

SPARK: Query-Aware Unstructured Sparsity with Recoverable KV Cache Channel Pruning

Huanxuan Liao^{T, μ}, Yixing Xu^α, Shizhu He^{T, μ*}, Guanchen Li^α, Xuanwu Yin^α, Dong Li^α, Emad Barsoum^α, Jun Zhao^{T, μ}, Kang Liu^{T, μ}

^αAdvanced Micro Devices (china) Co., Ltd.

^TInstitute of Automation, Chinese Academy of Sciences

^μUniversity of Chinese Academy of Sciences

liaohuanxuan2023@ia.ac.cn

Abstract

Long-context inference in large language models (LLMs) is increasingly constrained by the KV cache bottleneck: memory usage grows linearly with sequence length, while attention computation scales quadratically. Existing approaches address this issue by compressing the KV cache along the *temporal axis* through strategies such as token eviction or merging to reduce memory and computational overhead. However, these methods often neglect fine-grained importance variations across feature dimensions (i.e., the *channel axis*), thereby limiting their ability to effectively balance efficiency and model accuracy. In reality, we observe that channel saliency varies dramatically across both queries and positions: certain feature channels carry near-zero information for a given query, while others spike in relevance. To address this oversight, we propose SPARK, a training-free plug-and-play method that applies unstructured sparsity by pruning KV at the channel level, while dynamically restoring the pruned entries during attention score computation. Notably, our approach is orthogonal to existing KV compression and quantization techniques, making it compatible for integration with them to achieve further acceleration. By reducing channel-level redundancy, SPARK enables processing of longer sequences within the same memory budget. For sequences of equal length, SPARK not only preserves or improves model accuracy but also reduces KV cache storage by over 30% compared to eviction-based methods. Furthermore, even in an aggressive pruning ratio of 80%, SPARK maintains performance with less degradation than 5% compared to the based eviction method, demonstrating its robustness and effectiveness. Our code will be available at [Spark](#).

1 Introduction

Large language models (LLMs) are increasingly deployed in diverse and complex tasks requiring extended (even infinite) contextual understanding (Liu et al. 2025; Tan et al. 2025), such as book summarization (Kim et al. 2024), instruction following (Liao et al. 2024) and code or math reasoning (Liao et al. 2025b). To support these applications, recent models like GPT-4 (Achiam et al. 2023), Gemini-2.5 (Comanici et al. 2025), and Qwen-3 (Yang et al. 2025) have

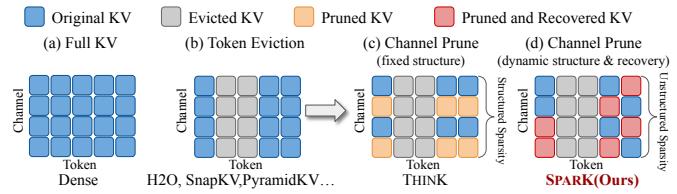


Figure 1: **Illustrative comparisons** among (a) full KV cache, (b) eviction-based KV compression, (c) structured channel pruning-based KV reduction, and (d) our proposed SPARK, which employs unstructured channel pruning with subsequent recovery during attention score computation.

scaled to 100K+ token contexts. However, handling such long sequences poses serious challenges in memory and latency due to the growing Key-Value (KV) cache in inference (Tang et al. 2024b). For example, storing the KV cache for 100K tokens in LLaMA3.1-8B (Dubey et al. 2024) exceeds 50GB, surpassing the model size itself (Shutova et al. 2025; Liao et al. 2025a). For a hidden size of 128, matrix multiplication latency increases from 2ms at 1K tokens to 764ms at 16K, nearly 380× slower. Consequently, KV cache has become a critical bottleneck, restricting the scalability and deployment of LLMs in long-context scenarios (Fu 2024).

Specifically, the total KV cache size is determined by the batch size B , sequence length S , number of layers L , attention heads N , and the head dimension D . Prior efforts on KV cache compression have primarily targeted the following aspects: 1) **Temporal axis (S)**: by evicting (Ge et al. 2023; Zhang et al. 2023) or merging (Wan et al. 2024; Wang et al. 2024) unimportant tokens using attention scores or redundancy heuristics (Cai et al. 2025). 2) **Spatial axis (L, N)**: by sharing KV across similar layers (Brandon et al. 2024; Wu and Tu 2024) or pruning attention heads with limited contribution to long-range dependencies (Xiao et al. 2025). 3) **Channel axis (D)**: by applying low-rank decomposition (Liu et al. 2024a; Sun et al. 2024a) or structured pruning (Xu et al. 2024). 4) **Quantization**: by applying low-bit precision storage (Hooper et al. 2024b; Zhang et al. 2025).

However, these approaches predominantly adopt structured channel sparsity, applying uniform pruning strategies that either discard or retain entire channels, or enforce fixed pruning masks across all tokens (Shi et al. 2024). Such meth-

*Corresponding author.

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ods rest on the assumption that channel importance remains consistent throughout the input sequence, which overlooks the dynamic and token-specific nature of attention in LLMs. Moreover, by applying identical pruning masks to both keys and queries, these methods fail to account for the asymmetric roles and token-wise variability in channel saliency, ultimately limiting the flexibility of the dot-product attention mechanism. Instead of directly discarding unimportant channels, we argue that *replacing unimportant channel entries with approximate or low-magnitude entries* can mitigate attention score distortion and maintain performance even under an aggressive pruning ratio.

In this paper, we propose SPARK, a method that introduces fine-grained query-aware unstructured sparsity to the KV cache while guaranteeing the recoverability of pruned channel entries. We reformulate channel pruning as a **critical channel set** selection problem aimed at maximizing aggregate saliency across selected channels. To this end, we introduce a lightweight metric to quantify the per-token, per-channel importance and adopt a greedy algorithm to solve the resulting optimization problem efficiently (Bi et al. 2024). To mitigate information loss under high pruning ratios, we further introduce a recovery mechanism that approximates the contributions of pruned channels through a recovery function \mathcal{F} during attention computation. This approximation ensures effective information retention without incurring additional memory cost. We additionally explore value cache pruning via a simple norm-based heuristic, showing promising results and paving the way for future refinement. Furthermore, we propose two ratio-free variants: group-based (SPARK-g) and top-p pruning (SPARK-p), demonstrating the flexibility and generality of SPARK.

Extensive experimental evaluations demonstrate the effectiveness of SPARK across a wide range of scenarios, benchmarks (Bai et al. 2024; Hsieh et al. 2024), and LLMs (Dubey et al. 2024; Yang et al. 2025). Importantly, SPARK is compatible with prior methods that optimize S , L and N . When integrated with token eviction strategies, SPARK not only preserves computational efficiency and achieves comparable or superior accuracy but also reduces KV cache storage by over 30%. Remarkably, even at high channel pruning ratio ($\geq 70\%$) while maintaining the same sequence length via token eviction methods such as SnapKV (Li et al. 2024) or PyramidKV (Yang et al. 2024a), SPARK maintains performance degradation within 5% compared to the based method, significantly outperforming THINK, which incurs a 47.6% accuracy loss under similar settings. Our main contributions are listed as follows:

- We propose SPARK, a novel training-free plug-and-play KV cache compression approach that introduces unstructured fine-grained sparsity along the channel dimension. We reformulate the pruning task as a critical channel set selection problem that aims to maximize the saliency contribution of preserved channels.
- We introduce an on-the-fly recovery mechanism that approximates the contribution of pruned channels during attention score computation using a lightweight function \mathcal{F} to mitigate information loss with little increasing memory

footprint or computational overhead.

- Extensive experiments show that our method consistently achieves remarkable effectiveness in various benchmarks and LLM. Notably, even when pruning 80% of the channels at the same sequence length, the performance degradation remains within 5%.

2 Related Work

Existing KV cache compression methods can be broadly categorized into three categories based on dimensions: **temporal-axis**, **spatial-axis**, and **channel-axis** methods.

Temporal-Axis Optimization reduces the sequence length S to alleviate the linear memory growth in long-context inference (Liao et al. 2025d; Liu et al. 2024b). *Token eviction* methods selectively remove low-contributing tokens based on attention scores (Li et al. 2024; Ge et al. 2023; Yang et al. 2024a; Liao et al. 2025c) or redundancy heuristics (Cai et al. 2025). *Token merging* techniques compress inputs by merging semantically similar tokens (Nawrot et al. 2024; Wan et al. 2024; Wang et al. 2024) or aggregating discarded ones (Hooper et al. 2024a; Zhang et al. 2024). Paged KV cache architectures, such as vLLM (Kwon et al. 2023), further enhance scalability via memory paging.

Spatial-Axis Optimization reduces redundancy by shrinking the number of layers L or heads N . Cross-layer sharing (Sun et al. 2024b; Yang et al. 2024b) enables KV reuse across layers, while MQA (Shazeer 2019) and GQA (Ainslie et al. 2023) share KV pairs across heads. Head optimization aims to prune attention heads that are less sensitive to long-range dependencies (Fu et al. 2024; Tang et al. 2024a; Zhu et al. 2024a), and DuoAttention (Xiao et al. 2025) specializes heads for retrieval or streaming to enhance efficiency.

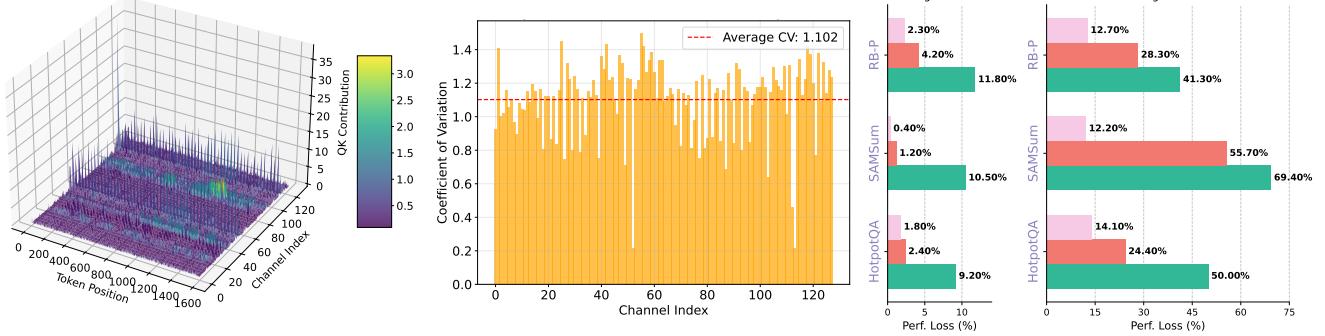
Channel-Axis Optimization targets the channel dimension D to reduce KV cache memory. Low-rank methods (Sun et al. 2024a; Zhu et al. 2024b) decompose KV matrices into compact representations, while MLA (Liu et al. 2024a) learns latent heads to compress channels, requiring retraining. Closest to our work, THINK (Xu et al. 2024) performs query-guided structured pruning, but its structured strategy significantly degrades performance under high pruning ratios. In contrast, we propose unstructured, dynamic pruning with on-the-fly recovery, enabling adaptive removal and restoration of KV entries during computation.

3 Preliminaries

LLM inference comprises two stages (Liu et al. 2025): **prefill** and **decode**. During prefill, the entire input sequence is processed in parallel to generate the first output token. Given a prompt embedding $\mathbf{X} \in \mathbb{R}^{S \times H}$, where S is the sequence length and H is the hidden dimension, the key and value matrices for each attention head $i \in [1, N]$ are computed as:

$$\mathcal{K}_i = \mathbf{X} \mathbf{W}_k^i, \quad \mathcal{V}_i = \mathbf{X} \mathbf{W}_v^i, \quad (1)$$

where $\mathbf{W}_k^i, \mathbf{W}_v^i \in \mathbb{R}^{H \times D}$ are the projection matrices for the i -th head, and D is the dimensionality of each head. The resulting keys and values are stored in the KV cache. During decode, each newly generated token embedding $\mathbf{x} \in \mathbb{R}^{1 \times H}$



(a) **3D surface visualization** of score contributions, highlighting token-wise unstructured activation patterns across channels, suggesting dynamic channel modulation for different contexts.

(b) **Coefficient of Variation (CV)** distribution across channels, suggesting dynamic caused by the method, highlighting the importance of unstructured pruning and recovery.

Figure 2: Rethinking the salience of key channels using LLaMA3.1-8B-Instruct (Dubey et al. 2024) on Longbench (Bai et al. 2024). All visualizations are derived from the 18th attention layer and the 0th attention head.

is projected to obtain the corresponding query, key, and value vectors and appended to the existing KV cache:

$$\mathbf{q}_i = \mathbf{xW}_q^i, \quad \mathbf{k}_i = \mathbf{xW}_k^i, \quad \mathbf{v}_i = \mathbf{xW}_v^i. \quad (2)$$

$$\mathcal{K}_i \leftarrow \text{Cat}[\mathcal{K}_i, \mathbf{k}_i], \quad \mathcal{V}_i \leftarrow \text{Cat}[\mathcal{V}_i, \mathbf{v}_i]. \quad (3)$$

The attention output for each head is then computed as:

$$\mathbf{a}_i = \text{Softmax} \left(\frac{\mathbf{q}_i \mathcal{K}_i^\top}{\sqrt{D}} \right), \quad \mathbf{o}_i = \mathbf{a}_i \mathcal{V}_i. \quad (4)$$

Finally, the outputs \mathbf{o}_i from all heads are concatenated and passed to the feed-forward network (FFN). In scenarios involving extended contexts or large batch processing, the primary bottlenecks in memory consumption and computational speed stem from the KV size. While existing approaches primarily focus on reducing KV size through temporal (S) or spatial (L, N) optimization, we draw inspiration from THINK (Xu et al. 2024) and propose optimizing the KV cache from channel D , thereby offering a complementary and orthogonal direction for KV compression.

4 Methodology

In this section, we begin with an experimental analysis and motivation for SPARK in Sec.4.1, followed by problem formulation and analysis in Sec.4.2. We further introduce the proposed SPARK in Sec.4.3.

4.1 Motivations and Observations

To understand the role of individual key channels, we conduct an empirical analysis¹ of the QK dot-product scores. As shown in Figure 2, we observe **unstructured, token-dependent channel** importance patterns that vary significantly across different tokens, which motivates the need for adaptive pruning strategies that can dynamically select different channels for different tokens, rather than applying uniform pruning across the entire sequence (Jie et al. 2025).

Observation 1: Token-wise Unstructured Channel Sparsity. Empirical analysis reveals that attention heads exhibit highly unstructured channel-wise sparsity, varying significantly across tokens. As shown in Figure 2(a), the 3D surface visualization highlights token-dependent activation patterns, where different tokens rely on distinct subsets of channels. This contradicts structured pruning assumptions where importance is globally consistent. To quantify this variability, we compute the coefficient of variation (CV) across tokens for each channel, as illustrated in Figure 2(b). The average CV exceeds 1.1, indicating that token-wise fluctuations dominate. This suggests that channel importance is highly context sensitive and cannot be accurately captured through a static and structured sparsity. Figure 2(c) further demonstrates that unstructured pruning, which respects token-level heterogeneity, substantially outperforms structured pruning. At 50% pruning, unstructured pruning leads to only 1.2% performance drop (vs. 4.2% for structured); at 80% pruning, it maintains a 27.4% gap (28.3% vs. 55.7%). These results affirm the necessity of unstructured sparsity.

Observation 2: Retaining Dimensional Structure Mitigates Pruning Impact. Figure 2(c) also shows that replacing pruned channel entries with minimal constant values (e.g., 0.01) during attention score computation rather than zeroing or omitting them yields substantial performance gains. This lightweight strategy preserves the structural integrity of the attention mechanism while avoiding pruning queries. Under 80% pruning, this approach significantly narrows the performance gap. On SAMSum, it reduces performance degradation from 55.7% to 12.2%; on HotpotQA, from 69.4% to 41.3%; and on RB-P, from 50.0% to 24.4%. On average, the substitution of entries reduces the loss of accuracy by 32.4% compared to removal. These results highlight that even a coarse query-agnostic constant of pruning channel can play a pivotal role in maintaining performance.

¹More analysis and metric details refer to the Appendix B.

4.2 Problem Formulation and Analysis

Let $\mathcal{C}_{i,t} = \{c_1, c_2, \dots, c_D\}$ denote the original channel set for each head i and token t , where D is the head dimension. We aim to select a subset $\hat{\mathcal{C}}_{i,t} \subseteq \mathcal{C}_{i,t}$ of T channels ($T \ll D$) that retain the most salient attention contributions, thereby enhancing inference efficiency while minimizing performance degradation. To formalize this, we introduce a binary mask $\mathcal{S}_{i,t} = \{z_{i,t}^1, \dots, z_{i,t}^D\} \in \{0, 1\}^D$ with $z_{i,t}^j \in \{0, 1\}$ indicating whether channel j is retained ($z_{i,t}^j = 1$) or pruned ($z_{i,t}^j = 0$). Our primary goal is to minimize the discrepancy (\mathcal{E}) in attention weights after pruning:

$$\min_{\mathcal{S}_{i,t}} \mathcal{E}(\mathcal{S}_{i,t}) = \|\mathbf{q}_{i,t}\mathbf{k}_{i,t}^\top - (\mathbf{q}_{i,t}\mathcal{S}_{i,t})(\mathbf{k}_{i,t}\mathcal{S}_{i,t})^\top\|_F, \quad (5)$$

where $\|\cdot\|_F$ denotes the Frobenius norm for vectors. Solving this combinatorial problem exactly is intractable as it corresponds to a cardinality-constrained low-rank approximation. To derive an approximate solution, we expand the squared Frobenius norm of \mathcal{E} for each token t :

$$\begin{aligned} \mathcal{E}(\mathcal{S}_{i,t})^2 &= \sum_{j=1}^D \|\mathbf{q}_{i,t}^j\|_2^2 \|\mathbf{k}_{i,t}^j\|_2^2 (1 - z_{i,t}^j)^2 + \\ &\quad 2 \sum_{\substack{j,r=1 \\ j < r}}^D \langle \mathbf{q}_{i,t}^j, \mathbf{q}_{i,t}^r \rangle \langle \mathbf{k}_{i,t}^j, \mathbf{k}_{i,t}^r \rangle (1 - z_{i,t}^j z_{i,t}^r), \end{aligned} \quad (6)$$

where $\mathbf{q}_{i,t}^j$ and $\mathbf{k}_{i,t}^j$ are the j -th dimensions of $\mathbf{q}_{i,t}$ and $\mathbf{k}_{i,t}$ respectively (similarly for r). The first term measures individual contributions of each pruned channel, while the second reflects inter-channel redundancy. In practice, we observe that different channels are nearly uncorrelated (i.e., $\langle \mathbf{k}_{i,t}^j, \mathbf{k}_{i,t}^r \rangle \approx 0$ for $j \neq r$), allowing us to drop the second term. Thus, minimizing $\mathcal{E}(\mathcal{S}_{i,t})$ is well-approximated by minimizing the sum of the norms of pruned channel contributions for each token, which is equivalent to maximizing retained channel scores while the number of selected channels for each token is fixed: $\sum_j^D z_{i,t}^j = T$. We introduce a proxy saliency score $w_{i,t}^j = \|\mathbf{q}_{i,t}^j\|_2 \|\mathbf{k}_{i,t}^j\|_2$, which upper bounds the contribution of channel j at token t to the Frobenius norm. The optimization problem is reformulated as follows:

$$\max_{\mathcal{Z}_{i,t}} \sum_{j=1}^D w_{i,t}^j z_{i,t}^j \quad \text{s.t.} \quad \sum_{j=1}^D z_{i,t}^j = T, \quad \forall t, \quad (7)$$

Since the objective is linear and additive in z_j , the optimal solution is simply to select the T channels with the highest saliency score w_j , which can be efficiently solved using a greedy algorithm: $\hat{\mathcal{C}}_{i,t} = \text{Top}_T(w_{i,t}^1, \dots, w_{i,t}^D)$. Given the pruning ratio λ , we only keep the $T = \lfloor (1 - \lambda)D \rfloor$ most important channels among D channels of each head.

4.3 SPARK

Building on above analysis, we redefine the channel pruning problem as (Eq. 6). Since this study focuses on efficiency in long-context inference, we employ a heuristic algorithm

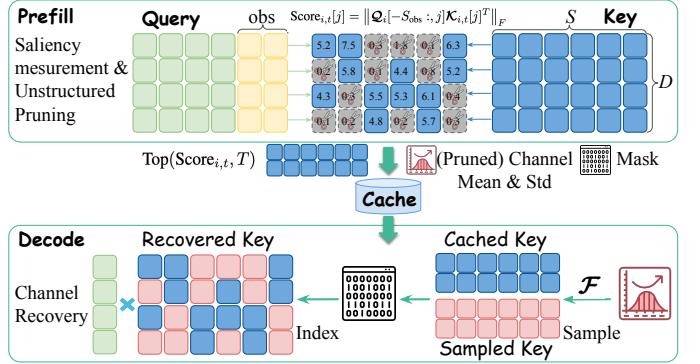


Figure 3: **An illustration of SPARK.** SPARK computes channel-wise saliency scores and applies unstructured pruning during prefill. During decoding, SPARK leverage \mathcal{F} and sampling from the cached distribution to reconstruct the pruned channels and then perform standard full attention.

with relatively low computational complexity to obtain an approximate solution. To this end, we introduce an unstructured channel pruning method (Figure 3), which selects an appropriate channel subset while ensuring that it satisfies the constraint. Our approach is training-free, plug-and-play, and model-agnostic, which makes it applicable to any LLM.

As illustrated in Figure 3, the proposed method consists of two primary phases: 1) unstructured channel pruning based on saliency measurement during **prefill**, and 2) channel recovery using stored distribution patterns during **decode**. Following previous work (Li et al. 2024; Xu et al. 2024), to reduce the computation cost, we only use the last observation window to calculate the saliency score. Specifically, we approximate the attention interaction by replacing per-token query vectors with the mean query vector computed over a local observation window. Specifically, for an observation window of size W , the mean query vector $\bar{\mathbf{q}}_i$ for the head i is calculated as the average of the query vectors $\mathbf{q}_{i,t}$ over the window: $\bar{\mathbf{q}}_i^j = \frac{1}{W} \sum_{t=t_0}^{t_0+W-1} \mathbf{q}_{i,t}^j$, where t_0 is the starting token index of the window.

Saliency Measurement and Unstructured Pruning. We compute the proxy saliency score $w_{j,t}$ for each channel j and token t to estimate per-channel contribution to the attention mechanism. We sort the scores in descending order and construct a binary pruning mask $\mathcal{S}_i \in \{0, 1\}^{S \times D}$ for head i , retaining the top- T channels. The pruned key matrix is denoted as $\hat{\mathcal{K}}_i = \mathcal{K}_i[\mathcal{S}_i] \in \mathbb{R}^{S \times T}$, where $\mathcal{K}_i[\mathcal{S}_i]$ extracts the channels indexed by \mathcal{S} . To support recovery during decoding, we further compute the distributional statistics² (mean μ_i , standard deviation σ_i) of the saliency scores, or the mean of pruned entries $\mu_{i,\text{pruned}}$. These statistics are critical for recovering approximations of the pruned channels as our goal is to select channels with lower final attention scores, rather than those with inherently small key entries, given the non-trivial dependency of scores on query key interactions.

Channel Recovery. Based on Observation 2 in Section 4.1,

²Detailed formulations are provided in Appendix A.2.

Method	Single-Document QA				Multi-Document QA				Summarization			Few-shot Learning			Synthetic		Code		
	NrtvQA	Qasper	MF-en	HopotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	Pre	Lcc	Rb-P	Avg.		
KV-size 128	Vanilla	22.48	44.72	46.23	48.49	44.71	24.43	30.7	22.8	27.28	72.0	88.35	42.28	6.5	72.0	63.61	51.67	44.27	
	StreamingLLM	13.64	18.03	17.79	31.36	27.46	8.67	17.31	18.99	17.87	31.0	31.21	35.71	1.5	67.5	56.63	55.16	28.11	
	ExpectedAttention	17.32	24.08	23.87	38.76	26.43	12.55	22.26	20.81	23.57	20.5	77.22	36.59	5.5	62.5	52.78	46.45	31.95	
	TOVA	17.09	23.35	37.88	43.32	28.68	15.85	19.87	20.54	18.51	26.5	85.18	39.15	4.0	60.5	59.98	57.17	34.85	
	SnapKV	15.29	20.03	29.2	39.92	28.26	15.06	17.74	19.27	18.05	21.0	68.64	36.64	6.0	66.0	57.86	59.08	32.38	
	+THINK (0.5)	13.6	19.2	31.78	36.24	25.05	11.92	16.85	19.17	16.4	2.0	50.73	32.8	6.0	65.0	52.29	52.11	28.20	
	+THINK (0.8)	7.6	7.03	17.45	19.98	9.8	6.9	14.37	14.15	12.5	0.0	21.36	11.22	1.02	63.0	30.42	34.69	16.97	
	+SPARK (0.5)	13.52	20.19	29.28	38.77	26.33	14.44	17.66	19.12	17.98	21.0	68.95	36.66	5.5	65.5	58.49	59.18	32.04	
	+SPARK (0.8)	13.82	20.28	28.63	40.84	26.75	14.25	17.29	19.06	17.23	22.0	57.2	35.41	7.0	64.0	57.2	57.61	31.16	
	PyramidKV	21.79	44.6	45.96	48.33	43.63	25.82	30.42	22.45	27.05	72.0	88.69	41.59	6.0	71.5	62.21	48.72	43.80	
KV-size 512	+THINK (0.5)	22.48	40.56	47.94	45.83	34.95	23.19	27.55	22.54	25.73	53.5	84.88	32.7	7.78	71.0	53.9	51.54	40.38	
	+THINK (0.8)	6.37	5.53	13.73	12.53	5.47	3.16	16.97	14.21	17.02	0.0	23.03	7.54	1.73	13.0	29.67	27.51	12.34	
	+SPARK (0.5)	22.66	43.95	45.82	48.33	43.85	24.85	30.16	22.76	26.84	70.0	88.34	41.4	6.5	71.5	62.83	51.15	43.81	
	+SPARK (0.8)	22.44	44.2	44.62	46.29	40.37	22.68	27.83	22.56	25.67	69.0	84.2	40.17	5.5	72.0	60.38	41.98	41.87	
	StreamingLLM	13.98	23.72	20.26	35.82	29.76	11.34	22.12	19.56	24.49	45.0	54.98	38.32	4.5	67.0	58.16	52.63	32.6	
	ExpectedAttention	19.73	33.41	30.2	45.06	32.81	20.43	25.55	21.45	26.25	51.0	85.76	39.57	6.0	56.0	62.0	54.84	38.13	
	TOVA	18.84	33.46	44.0	48.36	36.82	21.47	23.07	20.72	24.33	63.0	88.91	41.01	6.0	71.0	64.66	58.33	41.5	
	SnapKV	19.24	36.51	43.61	46.83	36.62	23.11	22.62	21.17	24.03	45.0	88.59	40.09	6.0	71.5	63.75	58.65	40.46	
	+THINK (0.5)	18.73	33.83	41.47	43.72	27.98	20.91	20.59	21.56	22.25	15.5	84.62	33.82	7.0	71.5	57.01	56.97	36.09	
	+THINK (0.8)	9.48	6.59	18.62	18.28	8.32	9.2	17.11	15.37	16.46	0.0	43.94	8.6	2.21	34.62	33.43	35.47	17.36	
	+SPARK (0.5)	18.66	36.13	43.23	46.66	36.17	22.86	22.44	21.19	23.7	42.5	89.11	40.15	6.5	71.5	63.8	59.0	40.22	
	+SPARK (0.8)	18.23	37.34	42.42	44.71	34.85	23.14	21.8	21.26	23.68	41.5	87.22	38.88	5.0	72.5	62.86	55.01	39.40	
	PyramidKV	21.79	44.6	45.96	48.33	43.63	25.82	30.42	22.45	26.96	72.0	88.69	41.59	6.0	71.5	62.21	48.72	43.79	
The choice of distribution is flexible and can be configured per head or globally. Empirically, degenerate sampling performs robustly across tasks and layers. Overall, the \mathcal{F} is defined as:	+THINK (0.5)	22.48	40.56	47.94	45.83	34.95	23.19	27.55	22.54	25.6	53.5	84.88	32.7	7.78	71.0	53.9	51.54	40.37	
	+THINK (0.8)	6.37	5.53	13.73	12.53	5.47	3.16	16.97	14.21	17.11	0.0	23.03	7.54	1.73	13.0	29.67	27.51	12.35	
	+SPARK (0.5)	22.79	43.99	45.63	48.83	43.64	24.87	30.34	22.89	26.57	70.0	88.75	42.28	6.5	71.5	62.72	50.81	43.88	
	+SPARK (0.8)	22.73	44.1	47.2	46.47	40.51	22.81	26.66	22.72	24.87	68.0	88.63	40.44	5.5	72.0	59.61	42.44	42.17	
	Finally, we reconstruct the full key matrix $\tilde{\mathcal{K}}_i$ by combining the cached pruned keys with the sampled keys according to the mask \mathcal{S}_i , ensuring both structural completeness and numerical consistency of the attention computation.																		

Table 1: Performance comparison on LLaMA-3-8B-Instruct at LongBench. **SPARK** (λ) and **THINK**(λ) denote the channel-wise key cache pruning ratio λ . Full results including other cache budgets and additional models are provided in Appendix F.2.

we propose a *query-aware recovery function* \mathcal{F} to reconstruct pruned key channels, addressing the limitations of discard or fixed-value replacement. We utilize cached distributional statistics collected during the prefill stage to sample plausible score values and then back-compute the corresponding key entries. Specifically, we sample a score $\tilde{w}_{j,t}$ and the sampled key entry is computed as $\tilde{k}_{i,t}^j = \frac{\tilde{w}_{i,t}^j}{\|\bar{q}_i^j\|_2}$, ensuring that the inner product $\langle \bar{q}_i^j, \tilde{k}_{i,t}^j \rangle \approx \tilde{w}_{i,t}^j$, consistent with the sampled score. We consider the following instantiations of the recovery function \mathcal{F} :

- Gaussian distribution:** $\tilde{w}_{i,t}^j \sim \mathcal{N}(\mu_i, \sigma_i^2)$
- Exponential distribution:** $\tilde{w}_{i,t}^j \sim \text{Exp}(1/\mu_i)$
- Degenerate (only μ) distribution:** $\tilde{w}_{i,t}^j = \mu_{i,\text{pruned}}$

The choice of distribution is flexible and can be configured per head or globally. Empirically, degenerate sampling performs robustly across tasks and layers. Overall, the \mathcal{F} is defined as:

$$\tilde{k}_{i,t}^j = \mathcal{F}(\mu, \sigma) = \frac{\text{sample}(\text{dist}(\mu, \sigma))}{\|\bar{q}_i^j\|_2}, \quad (8)$$

5 Experiments

5.1 Experimental Setup

Benchmark Datasets. We evaluate our SPARK against state-of-the-art KV cache compression methods on three widely recognized long-context understanding benchmarks: LongBench (Bai et al. 2024) and RULER (Hsieh et al. 2024) to thoroughly assess SPARK’s achievable performance.

Implementation Details. To validate SPARK’s general effectiveness, we evaluate on LLMs of varying scales and capabilities, including LLaMA-3/3.1-8/70B-Instruct (Dubey et al. 2024), Qwen3-8B/32B (Yang et al. 2025). To ensure a fair comparison between KV cache compression strategies and their integration with SPARK, we adopt consistent hyperparameter settings across all settings. Unless otherwise specified, we apply SPARK to the *key cache* only and use the *degenerate distribution* as the default recovery strategy.

Baselines. We benchmark SPARK against the standard full KV cache and prior KV cache compression methods, including StreamingLLM (Xiao et al. 2023), PyramidKV (Yang et al. 2024a), SnapKV (Li et al. 2024) and ExpectedAttention (Jegou et al. 2024) under various cache budgets. Additional experimental details can refer to Appendix C.

5.2 Benchmark on LongBench

Table 1 presents the performance comparison of KV compression methods and their integration with our proposed

Method	Niah1	Niah2	Niah3	MKey1	MKey2	MKey3	MValue	MQuery	VT	CWE	FWE	QA1	QA2	Avg.
Vanilla	100.0	100.0	100.0	99.6	100	99.2	99.1	99.0	99.8	88.9	90.0	81.0	57.2	93.36
StreamingLLM	18.8	17.4	19.0	20.2	20.0	18.4	18.25	18.2	32.84	0.18	81.33	31.4	33.6	25.35
ExpectedAttention	99.2	42.0	3.4	33.8	57.0	0.8	9.35	21.1	66.12	54.46	70.6	72.0	48.2	44.46
TOVA	100.0	100.0	97.8	99.4	96.8	0.4	98.9	99.25	99.76	54.04	90.8	77.4	54.6	82.24
SnapKV	100.0	100.0	10.0	99.8	97.2	63.2	97.7	99.45	97.36	53.92	85.73	80.8	57.2	80.18
+THINK(0.5)	96.6	99.6	9.4	99.0	92.2	55.4	98.55	98.25	94.84	29.12	88.87	76.0	50.6	76.03
+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.0	0.0	0.32	0.0	18.8	20.2	3.03
+SPARK(0.5)	100.0	100.0	10.2	99.4	96.6	62.8	98.05	99.45	97.64	53.8	86.2	80.8	56.0	80.07
+SPARK(0.8)	100.0	99.8	9.6	99.2	94.2	49.4	98.1	98.75	96.64	41.12	87.07	80.0	53.8	77.51
PyramidKV	100.0	100.0	5.0	99.8	98.2	55.0	98.6	99.35	98.6	16.88	87.0	80.0	57.2	76.59
+THINK(0.5)	97.2	100.0	4.8	99.4	93.0	49.2	98.7	98.75	96.16	8.46	88.33	76.2	52.4	74.05
+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.24	0.0	14.8	19.4	2.65
+SPARK(0.5)	99.2	99.2	5.2	99.4	97.6	54.4	97.95	98.7	98.16	16.84	86.27	79.6	56.8	76.1
+SPARK(0.8)	99.4	98.8	5.2	99.2	94.4	44.2	97.1	97.7	95.24	12.08	86.2	78.4	54.0	73.99

Table 2: RULER evaluation results on the LLaMA3.1-8B-Instruct model with SPARK under a 20% KV cache budget and 16K input length. Additional results across varying cache budgets and input lengths are reported in Appendix F.3 for completeness.

key cache channel pruning for LLaMA-3-8B-Instruct, evaluated in various KV budgets on the LongBench. The pruning ratio $\lambda = 0.8$ indicates that 80% of key cache channels are removed, resulting in a 40% reduction in the total KV cache memory. The following observations can be drawn:

Compatibility with Existing Methods. When integrated with token eviction strategies (e.g., PyramidKV), SPARK further boosts effectiveness. Comparisons between SnapKV and PyramidKV integrated with channel pruning further validate the robustness and general applicability of SPARK. Notably, the stronger the eviction strategy, the greater the gains observed from incorporating SPARK. Combining SPARK(0.5) outperforms the integrated eviction baseline and combining SPARK(0.8) maintains 95% of accuracy while reducing cache storage by 40%.

Superior Performance under High Pruning Ratios. SPARK consistently outperforms THINK across all budgets and pruning ratios. In particular, under a high pruning ratio ($\lambda = 0.8$), we observe that integrating THINK with either SnapKV or PyramidKV leads to substantial degradation in performance (average drop of **65%**). In contrast, combining SPARK with the same baselines incurs less than **5%** average performance loss. SPARK’s recoverable pruning preserves both expressivity and stability even at 80% sparsity, while THINK suffers catastrophic degradation.

5.3 Benchmark on RULER

Table 2 presents the results of RULER under 20% cache budget. SPARK consistently outperforms THINK while preserving competitive accuracy under all settings. Notably, under a stringent cache budget (20% or 50%) with 8K and 16K inputs, THINK (0.8) suffers drastic degradation with performance dropping below 3%, while SPARK (0.8) retains accuracy within 3% of baseline eviction methods, highlighting the effectiveness of our recovery mechanism. Even at moderate pruning (e.g., 0.5), SPARK consistently outperforms THINK and matches or surpasses baseline strategies, demonstrating both accuracy preservation and general applicability of our method SPARK.

5.4 Analysis

We conduct a comprehensive evaluation of SPARK across three key dimensions: pruning ratio, input length, and cache size. Results are summarized in Figure 4.

Impact of Pruning Ratio. Figure 4(a) shows that SPARK consistently outperforms THINK and the unrecovered variant, particularly under high compression. At $\lambda = 0.8$, THINK incurs a performance drop exceeding 35%, whereas SPARK maintains a degradation within 5%. This highlights the effectiveness of channel-aware pruning and query-aware recovery in preserving attention quality.

Throughput under Long Inputs. Figure 4(b) illustrates the decoding throughput across varying input lengths with KV budget of 128. While the full-cache baseline fails beyond 64k due to memory overflow, SPARK sustains high throughput across all lengths. Notably, SPARK achieves comparable throughput to THINK, despite the added recovery step. This indicates that the recovery mechanism introduces negligible overhead in decoding latency.

Cache Size vs. Performance. As shown in Figure 4(c), SPARK achieves superior performance under the same or smaller cache budgets. By pruning key channels, both SPARK and THINK achieve lower memory usage than SnapKV under the same KV size. Compared to THINK, SPARK consistently delivers performance closer to SnapKV across varying compression ratios. Under equal memory budgets, SPARK outperforms all baselines, underscoring its effectiveness in complementing KV compression methods for improved memory efficiency.

Pruning Value Cache Channels. We further extend SPARK to support simultaneous pruning of both key and value cache channels ($\lambda_k + \lambda_v$) in the Appendix D. As shown in Table 5, SPARK maintains strong robustness under joint pruning. For example, under the (0.5+0.5) configuration with SnapKV in 128 KV-size, the average performance drops marginally from 32.38 to 32.03, despite a further reduction in memory footprint. Notably, the results of (0.5 + 0.3) and (0.5 + 0.5) configuration achieve **comparable or even superior** performance to the (0.5) configuration. Although extreme com-

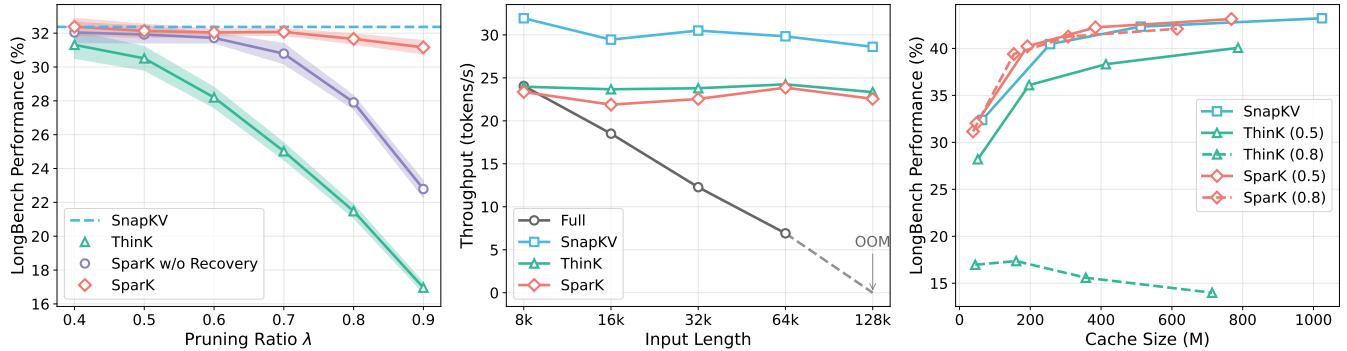


Figure 4: Performance–Efficiency analysis of SPARK on LLaMA3-8B-Instruct. (a) LongBench average performance under varying pruning ratios (λ). SPARK significantly outperforms THINK across all compression levels. (b) Throughput (tokens/s) with increasing input length. SPARK maintains stable decoding speed across long sequences (up to 128k) (c) Cache size vs. performance trade-off. SPARK achieves favorable efficiency–performance balance compared to THINK and SnapKV.

Dist.	$\lambda = 0.5$				$\lambda = 0.8$			
	128	512	1024	2048	128	512	1024	2048
	Norm. 32.71	39.76	41.37	42.18	31.25	38.78	41.03	41.68
Exp.	32.56	40.16	42.18	43.04	31.43	39.04	41.21	41.87
Deg.	32.04	40.22	42.24	43.13	31.16	39.41	41.26	42.09

Table 3: Ablation study on recovery distribution.

pression (0.8+0.8) leads to more noticeable accuracy drops, the recovery mechanism ensures that the additional loss remains within 5% on average. These results demonstrate that SPARK generalizes effectively to joint KV pruning, enabling greater memory savings under moderate settings while preserving task performance, and highlight the flexibility of our channel-wise sparsity and the critical role of recovery in maintaining accuracy.

5.5 Ablation Studies

Unless stated otherwise, all ablation experiments are conducted on the LongBench benchmark using the LLaMA3-8B-Instruct model with various KV budgets.

Recovery Distributions. We investigate the impact of different recovery distributions under two pruning ratios ($\lambda = 0.5$ and 0.8). As shown in Table 3, all three strategies Degenerate, Gaussian (Normal) and Exponential perform comparably, indicating that SPARK is robust to the choice of statistical modeling. Degenerate recovery outperforms other strategies, particularly on long inputs, suggesting its stability under aggressive pruning. While Gaussian and Exponential offer moderate flexibility, they tend to introduce slight noise that may not always benefit attention approximation when key is highly limited. The exponential distribution yields slightly better results at short sequences, likely due to its heavier tail offering greater diversity in sampled keys.

Adaptive Variants of SPARK. We further explore two adaptive variants of SPARK that remove the need for a pre-defined pruning ratio. The first variant, SPARK-p, applies a top- p thresholding strategy by greedily selecting the min-

Variants	Pruning Ratio (λ)	Threshold (p)	Group (g)	KV-Size				Overall Ratio
				128	512	1024	2048	
SPARK	0.5	-	-	32.04	40.22	42.24	43.13	0.50
SPARK-p	-	99%	-	32.11	40.13	42.18	42.95	0.58
SPARK-g	-	-	5	32.06	40.17	42.17	42.76	0.55
SPARK-g	-	-	4	32.11	40.11	42.45	43.27	0.44

Table 4: Ablation study on variants.

imum number of salient channels per token that cumulatively account for 99% of the total saliency. The second variant, SPARK-g, groups the D channels into g disjoint segments with ascending importance and assigns progressively larger pruning ratios to less salient groups. Specifically, for $g = 4$, we assign pruning ratios of (0.25, 0.5, 0.75, 1.0); for $g = 5$, we use (0.1, 0.3, 0.5, 0.7, 0.9). As shown in Table 4, both variants achieve comparable accuracy to the fixed-ratio baseline, while offering greater flexibility. Notably, the grouped variant with $g = 4$ achieves the highest overall performance (43.27 at 2048 input length) with a lower average pruning ratio (0.44), suggesting that fine-grained structured sparsity can lead to better trade-offs between compression and performance. These results underscore the potential of SPARK as a flexible and extensible framework for KV compression.

6 Conclusion

In this paper, we introduce SPARK, a novel channel-wise pruning that leverages unstructured sparsity alongside a lightweight statistical recovery mechanism. Unlike prior methods that suffer from significant degradation under high pruning ratios, SPARK preserves attention fidelity by selectively retaining salient channels and reconstructing pruned entries using cached statistics. Extensive experiments demonstrate that SPARK significantly reduces memory consumption and maintains competitive performance, highlighting the importance of channel recovery in mitigating the adverse effects of aggressive pruning.

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A SPARK

A.1 Error Objective Expansion

Our goal is to minimize the attention discrepancy after pruning, measured by the Frobenius norm between the original and pruned attention matrices:

$$\min_{\mathcal{S}_{i,t}} \mathcal{E}(\mathcal{S}_{i,t}) = \|\mathbf{q}_{i,t}\mathbf{k}_{i,t}^\top - (\mathbf{q}_{i,t}\mathcal{S}_{i,t})(\mathbf{k}_{i,t}\mathcal{S}_{i,t})^\top\|_F. \quad (9)$$

This objective is combinatorial and difficult to solve exactly. To enable efficient channel selection, we expand the squared Frobenius norm. Let $\mathbf{q}_{i,t}[j]$ and $\mathbf{k}_{i,t}[j]$ denote the j -th channel vector of query and key, respectively. Using the identity

$$\|A - B\|_F^2 = \|A\|_F^2 + \|B\|_F^2 - 2\langle A, B \rangle,$$

we can rewrite the squared error as:

$$\begin{aligned} & \mathcal{E}^2(\mathcal{S}_{i,t}) \\ &= \sum_{j=1}^D \sum_{r=1}^D \langle \mathbf{q}_{i,t}[j], \mathbf{q}_{i,t}[r] \rangle \langle \mathbf{k}_{i,t}[j], \mathbf{k}_{i,t}[r] \rangle (1 - \mathbf{z}_{j,t} \mathbf{z}_{r,t}) \\ &= \sum_{j=1}^D \|\mathbf{q}_{i,t}[j]\|_2^2 \|\mathbf{k}_{i,t}[j]\|_2^2 (1 - \mathbf{z}_{j,t}) \\ &\quad + 2 \sum_{\substack{j,r=1 \\ j < r}}^D \langle \mathbf{q}_{i,t}[j], \mathbf{q}_{i,t}[r] \rangle \langle \mathbf{k}_{i,t}[j], \mathbf{k}_{i,t}[r] \rangle (1 - \mathbf{z}_{j,t} \mathbf{z}_{r,t}). \end{aligned} \quad (10)$$

A.2 Caching Pruned Channel Statistics

Specifically, for each attention head i , first, we identify the set of channels that were pruned after the Top- T selection. Let this set of pruned channel indices be $\mathcal{C}_{i,\text{pruned}} = \mathcal{C}_i \setminus \hat{\mathcal{C}}_i$. We then compute the distribution statistics for the saliency scores $\mathbf{w}_{i,j}$ of all channels within the pruned set $\mathcal{C}_{i,\text{pruned}}$: Mean ($\mu_{i,\text{pruned}}$):

$$\mu_{i,\text{pruned}} = \frac{1}{|\mathcal{C}_{i,\text{pruned}}|} \sum_{j \in \mathcal{C}_{i,\text{pruned}}} \mathbf{w}_{i,j} \in \mathbb{R}^S \quad (11)$$

Mean (μ_i):

$$\mu_i = \frac{1}{|\mathcal{C}_i|} \sum_{j \in \mathcal{C}_i} \mathbf{w}_{i,j} \in \mathbb{R}^S \quad (12)$$

Standard Deviation (σ_i):

$$\sigma_i = \sqrt{\frac{1}{|\mathcal{C}_i|} \sum_{j \in \mathcal{C}_i} (\mathbf{w}_{i,j} - \mu_i)^2} \quad (13)$$

Then these calculated statistics (μ_i and σ_i , or possibly just the mean of the pruned channels $\mu_{i,\text{pruned}}$) are cached. In later stages, when it's necessary to recover or compensate for the impact of pruned channels, these statistics enable the generation of more reasonable compensation values, mitigating performance degradation that would result from simple zero or constant padding.

B Observations

B.1 Coefficient of Variation (CV)

The Coefficient of Variation (CV) is a standardized statistical measure that quantifies the relative variability of a dataset by expressing the standard deviation as a proportion of the mean. Formally, for a random variable X with mean μ and standard deviation σ , the CV is defined as:

$$CV = \frac{\sigma}{\mu} = \frac{\sqrt{\mathbb{E}[(X - \mu)^2]}}{\mathbb{E}[X]} \quad (14)$$

This dimensionless metric enables direct comparison of variability across datasets with different scales and units, making it particularly suitable for analyzing heterogeneous patterns in neural network activations.

The CV analysis is particularly necessary for key channel pattern analysis because: (1) it captures the context-sensitivity of individual channels by measuring how much their contributions vary across different input tokens; (2) it provides a scale-invariant measure that allows comparison across channels with different activation magnitudes; and (3) it enables systematic categorization of channels based on their behavioral patterns, informing adaptive compression strategies.

In our context, we employ CV to quantify the variability of channel-wise attention key activations across tokens. High CV values indicate that the importance of a given channel varies significantly with the input context, suggesting that a globally fixed importance ranking may be insufficient. This motivates the use of token-dependent, dynamic channel pruning strategies over static, globally ranked pruning. Therefore, CV provides a principled criterion for evaluating the necessity of fine-grained, context-aware channel selection in our method.

B.2 Token-Specific Channel Activation Patterns

To gain deeper insight into how different channels contribute to the attention computation, we visualize the QK scores across channel indices for representative tokens in Figure 5 and heatmap of channels in Figure 6.

C Implementation

For all tasks, we use a batch size of 1 for evaluation and follow the settings of the based eviction method. For instance, when comparing SnapKV and SnapKV integrated with THINK, we used a maximum pooling kernel size of 7 and an observation window size of 32, maintaining the same KV size for both configurations. For the RULER benchmark (Hsieh et al. 2024), we adopt 10 repetitions for each test unit and use context lengths of 16k and 8k. We implement all experiments in PyTorch (Paszke 2019) and Flash Attention (Dao 2024).

D Pruning Value Cache Channels

Unlike keys, value vectors cannot be assessed using the query for their relative importance, which makes structured pruning strategies such as those used in THINK (Xu et al. 2024) less suitable. To address this limitation, we adopt an

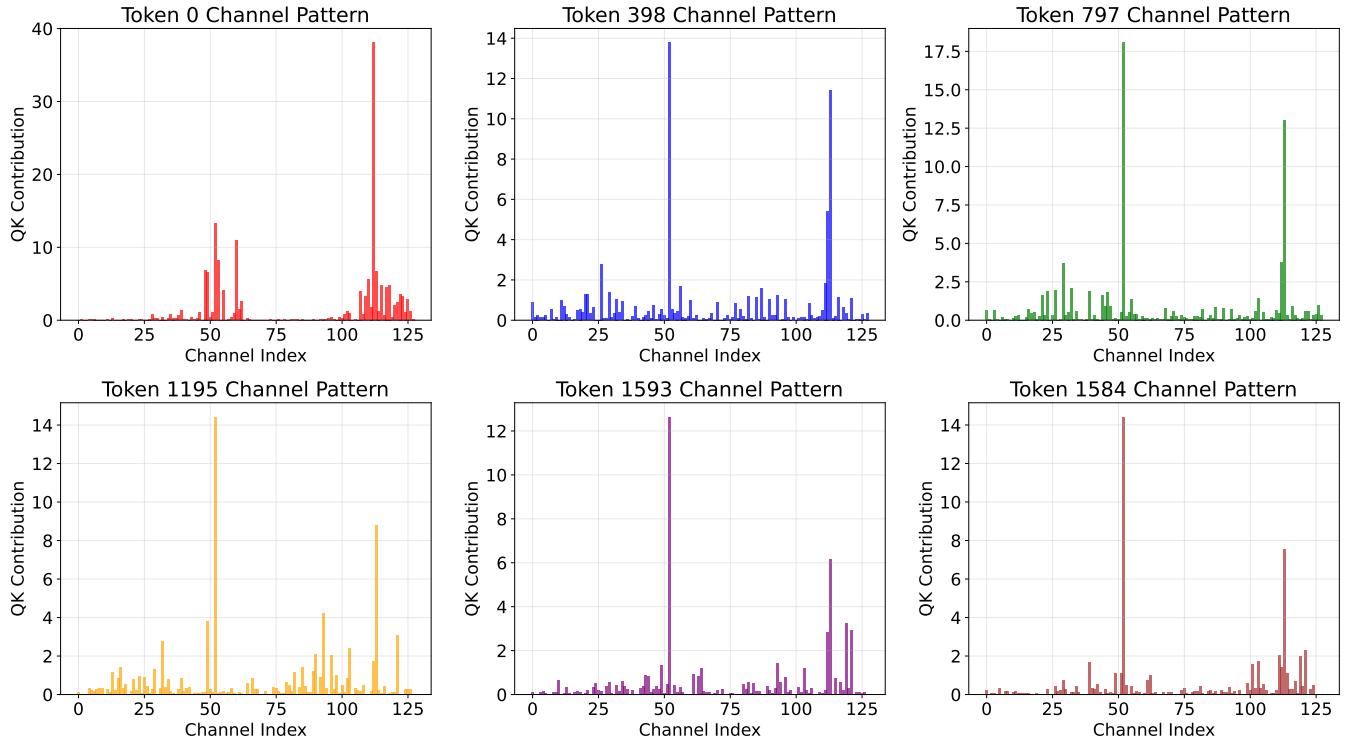


Figure 5: Visualization of QK-score distributions across channel indices for 6 representative tokens. Brighter hues indicate higher attention contributions, revealing: (1) Position-dependent sparsity (e.g., Token 0 vs 1195), (2) Task-critical channel clustering, (3) High variance in salient channel indices.

unstructured sparsity approach that better aligns with the distributional characteristics of value channels.

Specifically, for each token t , we estimate the importance score of each value channel $v_{i,t}^j$ denotes the j -th channel at head i . This norm-based scoring captures per-channel activation strength, allowing us to identify and prune the least informative dimensions in a fine-grained manner. We then apply the same masking and recovery mechanism as in key pruning: pruned channels are removed from the cache, and only the top- T channels (according to the norm) are retained. Unlike key recovery, value recovery requires no additional operations such as scaling or recombination, as values are directly consumed in the final weighted sum. This greatly simplifies the recovery process and reduces runtime overhead. The full results on LLaMA-3-8B-Instruct are in the Table 5.

While this norm-based criterion offers a practical and lightweight solution, it does not fully capture the semantics of value representations. We leave the exploration of more sophisticated pruning strategies—potentially leveraging attention weights, value-token correlations, or dynamic token importance—for future work.

E Limitations

Increased Computational Overhead. Although our recovery mechanism enables accurate reconstruction of pruned channels, it inevitably introduces additional computations

during attention score estimation. This overhead, while lightweight in steady-state throughput, contributes to increased Time-To-First-Token (TTFT), particularly in low-latency applications or systems with stringent serving constraints.

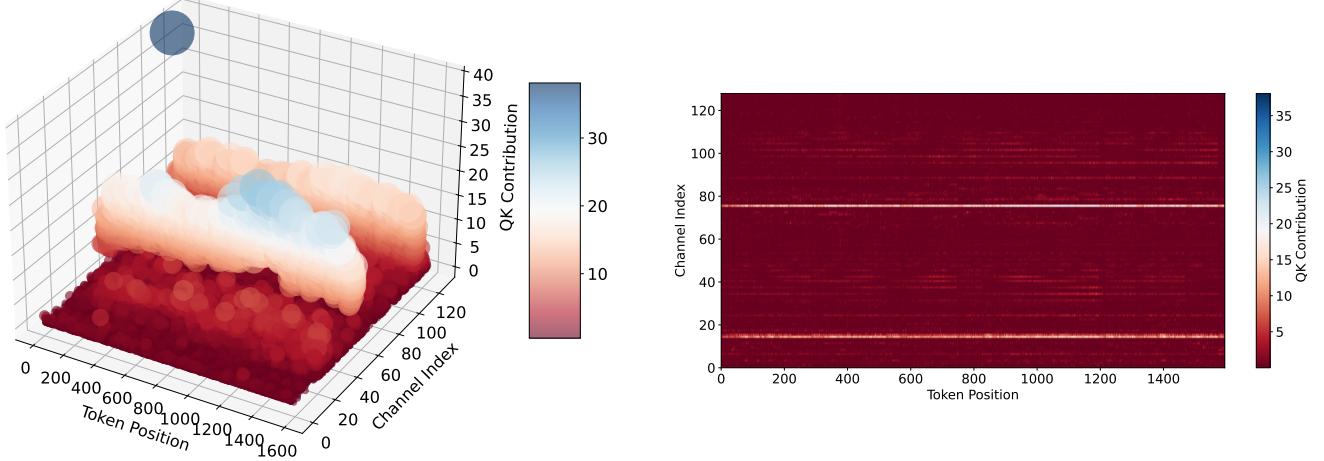
Limited Gains on Short Inputs. Our method is primarily designed to improve efficiency under long input sequences and large KV cache budgets. In contrast, for short inputs (e.g., $\leq 4k$ tokens), the memory footprint is already minimal, and the overhead introduced by dynamic channel scoring and recovery may outweigh the benefits. In such cases, static caching or lightweight token-eviction strategies may offer better latency-efficiency trade-offs.

Heuristic-Based Value Pruning. While our channel-wise pruning for the key cache is guided by query-aware saliency, the value cache pruning currently relies on simple norm-based heuristics. This limits its ability to fully exploit the semantic structure of value representations. Future work could explore task- or position-adaptive value pruning strategies.

F Extended Results

F.1 Memory Efficiency Analysis

To further assess the memory efficiency of our method, we conduct a peak memory usage analysis under varying batch sizes using the LLaMA-3.1-8B-Instruct model. We compare the full KV cache baseline with SPARK under different pruning ratios (0.5 and 0.8). Results are summarized in



(a) **3D scatter visualization** of score contributions, highlighting token-wise unstructured sparsity.

(b) **Heatmap visualization** of channel distribution across channels.

Figure 6: More visualizations for motivations of layer 18 and head 0.

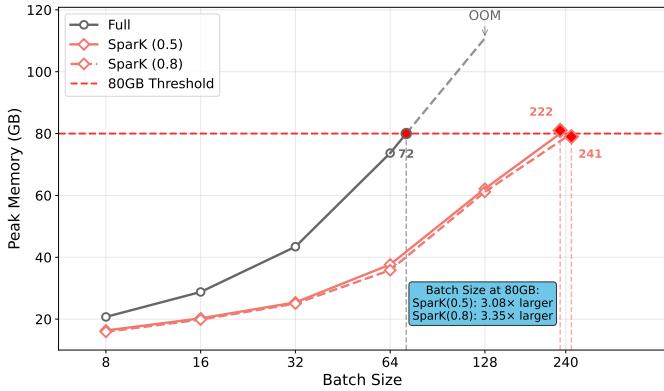


Figure 7: **Batch Size and Memory.** SPARK enables a 300% larger batch size, saving more than 20GB memory.

Figure 7.

Substantial Memory Reduction. Across all batch sizes, SPARK consistently reduces peak memory consumption compared to the full KV cache. At batch size 32, the full cache consumes 43.41 GB, while SPARK (0.5) and SPARK (0.8) reduce it to 25.41 GB and 25.02 GB, respectively. At batch size 64, memory drops from 73.69 GB to 37.65 GB (SPARK-0.5) and 35.83 GB (SPARK-0.8), indicating a $\sim 50\%$ reduction.

Scalability under Memory Constraints. We additionally measure the maximum supported batch size under an 80GB memory cap: Full KV cache supports only 72 batch sizes, SPARK (0.5) supports up to 222 batch sizes, SPARK (0.8) supports up to 241 batch sizes. This highlights SPARK’s effectiveness in enabling larger batch inference under fixed hardware budgets, improving throughput by over 3 \times with-

out sacrificing quality.

F.2 Longbench

To further validate the generality and robustness of our method, we conduct extensive experiments on the LongBench benchmark across multiple open-source LLMs with varying model scales and instruction-following capabilities. Specifically, Table 6 presents results on LLaMA3-8B-Instruct, while Tables 7, 8, 9, and 10 extend the evaluation to LLaMA3.1-8B, LLaMA3.1-70B, Qwen3-8B, and Qwen3-32B, respectively.

F.3 RULER

To further assess SPARK’s robustness under extreme long-context settings, we evaluate its performance on the RULER benchmark with 8K and 16K input lengths under various cache budgets (20% and 50%). The results are reported in Table 11.

Together, these results reinforce the compatibility of our method with diverse LLM architectures and its potential as a plug-and-play component for long-context optimization.

Method	Single-Document QA				Multi-Document QA				Summarization				Few-shot Learning				Synthetic		Code	
	NrtyQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PRe	Lcc	Avg PRg				
LLaMA-3-8B-Instruct, KV-size 128																				
SnapKV	15.29	20.03	29.2	39.92	28.26	15.06	17.74	19.27	18.05	21.0	68.64	36.64	6.0	66.0	57.86	59.08	32.38			
+SPARK (0.5)	13.52	20.19	29.28	38.7	26.33	14.44	17.66	19.12	17.98	21.0	68.9	36.66	5.5	65.5	58.49	59.18	32.04			
+SPARK (0.5 + 0.3)	13.54	20.59	28.24	39.6	26.01	14.07	17.63	19.36	17.87	21.0	67.6	36.12	7.5	67.5	56.02	56.04	31.8			
+SPARK (0.5 + 0.5)	13.68	20.28	29.95	40.4	26.34	13.16	17.4	19.38	17.43	21.0	71.5	36.23	7.5	66.5	55.77	55.88	32.03			
+SPARK (0.8)	13.82	20.28	28.63	40.8	26.75	14.25	17.29	19.06	17.23	22.0	57..	35.41	7.0	64.0	57.2	57.61	31.16			
+SPARK (0.8 + 0.3)	13.81	19.48	29.32	41.5	24.07	14.96	17.19	19.05	17.72	21.0	59.7	35.69	6.5	65.0	54.43	55.17	30.91			
+SPARK (0.8 + 0.8)	13.39	19.41	29.28	37.0	24.53	11.78	16.06	18.68	15.61	18.0	63.5	31.52	6.09	63.5	49.85	52.04	29.4			
PyramidKV	21.79	44.6	45.96	48.33	43.63	25.82	30.42	22.45	27.05	72.0	88.69	41.59	6.0	71.5	62.21	48.72	43.8			
+SPARK (0.5)	22.66	43.95	45.82	48.3	43.85	24.85	30.16	22.76	26.84	70.0	88.3	41.4	6.5	71.5	62.83	51.15	43.81			
+SPARK (0.5 + 0.3)	21.97	43.67	45.69	48.8	44.04	26.49	30.09	22.76	26.98	71.5	88.1	41.86	5.5	72.0	61.99	51.83	43.96			
+SPARK (0.8)	22.44	44.2	44.62	46.2	40.37	22.68	27.83	22.56	25.67	69.0	84..	40.17	5.5	72.0	60.38	41.98	41.87			
+SPARK (0.8 + 0.3)	23.59	42.82	46.72	46.8	40.38	22.66	28.4	22.82	26.38	67.5	88.4	39.96	6.0	72.0	60.89	44.66	42.51			
+SPARK (0.8 + 0.8)	19.0	37.38	45.83	42.0	34.14	19.39	23.04	21.73	24.01	64.0	87.9	36.42	3.83	70.5	56.49	57.01	40.17			
LLaMA-3-8B-Instruct, KV-size 512																				
SnapKV	19.24	36.51	43.61	46.83	36.62	23.11	22.62	21.17	24.03	45.0	88.59	40.09	6.0	71.5	63.75	58.65	40.46			
+SPARK (0.5)	18.66	36.13	43.23	46.6	36.17	22.86	22.44	21.19	23.7	42.5	89.1	40.15	6.5	71.5	63.8	59.0	40.22			
+SPARK (0.5 + 0.3)	18.89	36.42	42.27	46.1	37.1	21.89	22.33	21.36	23.54	43.0	88.4	40.23	5.5	71.5	61.89	56.65	39.83			
+SPARK (0.5 + 0.5)	17.66	36.29	44.12	48.0	36.33	22.72	21.7	21.48	23.07	42.5	88.5	39.29	5.0	71.5	62.74	59.51	40.03			
+SPARK (0.8)	18.23	37.34	42.42	44.7	34.85	23.14	21.8	21.26	23.68	41.5	87.2	38.88	5.0	72.5	62.86	55.01	39.40			
+SPARK (0.8 + 0.3)	18.02	35.92	42.88	44.8	33.93	23.64	21.14	21.34	23.43	41.5	87..	38.57	5.0	72.0	61.4	53.22	39.01			
+SPARK (0.8 + 0.8)	16.08	28.99	41.35	40.5	30.7	20.85	19.55	20.88	21.15	34.5	85.9	35.8	3.9	68.5	54.49	57.92	36.32			
PyramidKV	21.79	44.6	45.96	48.33	43.63	25.82	30.42	22.45	26.96	72.0	88.69	41.59	6.0	71.5	62.21	48.72	43.79			
+SPARK (0.5)	22.79	43.99	45.63	48.8	43.64	24.87	30.34	22.89	26.57	70.0	88.7	42.28	6.5	71.5	62.72	50.81	43.88			
+SPARK (0.5 + 0.3)	21.92	43.78	45.89	49.3	43.54	26.29	29.92	22.73	26.85	71.5	88.0	41.57	5.5	71.5	62.03	52.26	43.92			
+SPARK (0.8)	22.73	44.1	47.2	46.4	40.51	22.81	26.66	22.72	24.87	68.0	88.6	40.44	5.5	72.0	59.61	42.44	42.17			
+SPARK (0.8 + 0.3)	22.87	42.99	46.23	46.9	40.03	23.15	28.06	22.76	26.0	67.5	88..	39.92	5.5	72.5	60.89	44.56	42.42			
+SPARK (0.8 + 0.8)	19.01	36.61	46.44	41.9	34.64	19.24	23.13	21.66	24.02	64.0	87.9	36.19	3.33	70.5	56.29	55.75	40.04			
LLaMA-3-8B-Instruct, KV-size 1024																				
SnapKV	21.39	39.89	44.54	48.78	43.51	23.76	24.61	21.92	25.64	55.5	88.51	40.79	6.0	72.5	63.76	56.05	42.32			
+SPARK (0.5)	21.9	38.92	45.22	48.6	41.27	24.25	24.65	21.92	25.88	55.0	88..	41.22	6.5	72.0	63.43	56.22	42.24			
+SPARK (0.5 + 0.3)	20.13	38.5	43.06	47.5	41.82	24.36	24.13	21.03	25.62	54.5	85.7	40.45	6.0	71.5	61.4	53.17	41.18			
+SPARK (0.5 + 0.5)	21.28	38.17	45.04	46.1	37.97	24.34	22.81	20.15	24.96	50.5	85.4	39.3	6.0	70.0	59.58	52.92	40.29			
+SPARK (0.8)	21.26	39.65	45.48	46.9	38.85	22.84	23.98	21.94	25.37	54.0	87.9	39.34	5.0	72.0	63.66	51.97	41.26			
+SPARK (0.8 + 0.3)	21.02	37.3	46.12	44.1	36.79	22.97	22.31	20.59	24.54	51.0	85.4	38.89	4.5	73.5	58.04	48.65	39.74			
+SPARK (0.8 + 0.8)	15.74	32.07	40.23	34.5	33.89	19.33	20.08	19.54	21.92	46.5	79.3	33.1	3.9	61.5	52.68	53.42	35.49			
PyramidKV	21.79	44.6	46.0	48.33	43.63	25.82	30.42	22.45	26.53	72.0	88.69	41.59	6.0	71.5	61.87	48.72	43.75			
+SPARK (0.5)	22.53	43.84	45.97	47.8	43.64	24.87	30.06	22.9	26.82	70.0	89.2	41.87	6.5	71.5	61.4	50.84	43.74			
+SPARK (0.5 + 0.3)	21.78	43.49	45.99	49.6	43.46	26.32	30.07	22.6	26.49	71.5	88.1	41.92	5.5	72.0	61.96	51.76	43.92			
+SPARK (0.8)	22.59	44.35	47.66	47.1	39.96	22.94	28.04	22.68	25.37	68.5	88.6	40.62	5.5	72.5	57.89	43.28	42.35			
+SPARK (0.8 + 0.3)	23.19	43.03	47.13	46.2	40.3	23.47	28.54	22.59	25.94	68.0	87.9	40.34	6.0	72.5	60.24	44.3	42.49			
+SPARK (0.8 + 0.8)	19.36	36.94	45.03	41.8	33.47	20.29	23.05	21.75	23.47	64.5	88.0	36.09	3.33	69.0	55.15	56.56	39.87			
LLaMA-3-8B-Instruct, KV-size 2048																				
SnapKV	22.66	41.71	46.74	48.86	43.68	23.76	27.09	22.39	27.28	62.0	88.3	41.45	6.0	72.0	63.64	53.8	43.21			
+SPARK (0.5)	22.98	40.11	46.65	48.8	42.48	23.97	27.24	22.27	26.95	61.5	88.6	41.45	6.5	72.0	63.57	54.77	43.13			
+SPARK (0.5 + 0.3)	23.06	40.75	45.87	49.1	43.43	24.92	26.91	22.15	27.05	60.0	87.5	40.94	6.0	71.5	61.9	53.97	42.82			
+SPARK (0.5 + 0.5)	22.82	41.78	46.32	47.9	40.56	23.86	26.16	22.32	26.75	60.5	88.9	40.94	7.0	71.5	62.52	56.11	42.88			
+SPARK (0.8)	23.65	41.91	46.59	47.1	41.33	21.84	25.99	22.58	26.81	59.0	88.0	39.62	5.0	72.5	62.74	48.69	42.09			
+SPARK (0.8 + 0.3)	21.88	41.94	46.18	47.1	38.95	22.62	25.41	22.29	25.74	59.0	88.5	39.96	4.5	72.5	61.22	47.0	41.55			
+SPARK (0.8 + 0.8)	18.68	34.6	45.04	42.4	35.95	20.52	22.27	21.58	23.65	61.0	88.5	34.3	3.33	70.0	57.18	57.6	39.79			
PyramidKV	23.7	42.37	45.43	48.7	43.73	22.86	26.65	22.16	26.73	60.5	88.44	41.36	6.0	72.0	61.91	50.23	42.67			
+SPARK (0.5)	23.3	40.47	41.47	47.7	43.38	23.49	25.5	21.85	25.49	59.5	88.0	41.41	6.0	71.0	61.79	51.52	41.99			
+SPARK (0.5 + 0.3)	22.89	41.54	46.6	48.3	42.98	21.75	26.11	22.14	26.78	60.0	87.8	41.38	5.5	71.0	62.14	53.62	42.54			
+SPARK (0.8)	21.93	41.48	45.24	46..	41.5	22.38	23.08	21.74	25.83	55.5	86.7	39.72	5.0	72.5	59.55	44.35	40.8			
+SPARK (0.8 + 0.3)	21.0	40.12	46.12	47.4	39.06	19.7	24.9	22.09	26.38	58.5	87.9	40.17	4.5	71.5						

Method	Single-Document QA				Multi-Document QA				Summarization			Few-shot Learning			Synthetic		Code		
	NrtyQA	Qasper	MF-en	HopotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	Pre	Lcc	Rb-P	Avg.		
KV-size 128	Vanilla	22.48	44.72	46.23	48.49	44.71	24.43	30.7	22.8	27.28	72.0	88.35	42.28	6.5	72.0	63.61	51.67	44.27	
	StreamingLLM	13.64	18.03	17.79	31.36	27.46	8.67	17.31	18.99	17.87	31.0	31.21	35.71	1.5	67.5	56.63	55.16	28.11	
	ExpectedAttention	17.32	24.08	23.87	38.76	26.43	12.55	22.26	20.81	23.57	20.5	77.22	36.59	5.5	62.5	52.78	46.45	31.95	
	TOVA	17.09	23.35	37.88	43.32	28.68	15.85	19.87	20.54	18.51	26.5	85.18	39.15	4.0	60.5	59.98	57.17	34.85	
	SnapKV	15.29	20.03	29.2	39.92	28.26	15.06	17.74	19.27	18.05	21.0	68.64	36.64	6.0	66.0	57.86	59.08	32.38	
	+THINK (0.5)	13.6	19.2	31.78	36.24	25.05	11.92	16.85	19.17	16.4	2.0	50.73	32.8	6.0	65.0	52.29	52.11	28.20	
	+THINK (0.8)	7.6	7.03	17.45	19.98	9.8	6.9	14.37	14.15	12.5	0.0	21.36	11.22	1.02	63.0	30.42	34.69	16.97	
	+SPARK (0.5)	13.52	20.19	29.28	38.77	26.33	14.44	17.66	19.12	17.98	21.0	68.95	36.66	5.5	65.5	58.49	59.18	32.04	
	+SPARK (0.8)	13.82	20.28	28.63	40.84	26.75	14.25	17.29	19.06	17.23	22.0	57.2	35.41	7.0	64.0	57.2	57.61	31.16	
	PyramidKV	21.79	44.6	45.96	48.33	43.63	25.82	30.42	22.45	27.05	72.0	88.69	41.59	6.0	71.5	62.21	48.72	43.8	
KV-size 512	+THINK (0.5)	22.48	40.56	47.94	45.83	34.95	23.19	27.55	22.54	25.73	53.5	84.88	32.7	7.78	71.0	53.9	51.54	40.38	
	+THINK (0.8)	6.37	5.53	13.73	12.53	5.47	3.16	16.97	14.21	17.02	0.0	23.03	7.54	1.73	13.0	29.67	27.51	12.34	
	+SPARK (0.5)	22.66	43.95	45.82	48.33	43.85	24.85	30.16	22.76	26.84	70.0	88.34	41.4	6.5	71.5	62.83	51.15	43.81	
	+SPARK (0.8)	22.44	44.2	44.62	46.29	40.37	22.68	27.83	22.56	25.67	69.0	84.2	40.17	5.5	72.0	60.38	41.98	41.87	
	StreamingLLM	13.98	23.72	20.26	35.82	29.76	11.34	22.12	19.56	24.49	45.0	54.98	38.32	4.5	67.0	58.16	52.63	32.6	
	ExpectedAttention	19.73	33.41	30.2	45.06	32.81	20.43	25.55	21.45	26.25	51.0	85.76	39.57	6.0	56.0	62.0	54.84	38.13	
	TOVA	18.84	33.46	44.0	48.36	36.82	21.47	23.07	20.72	24.33	63.0	88.91	41.01	6.0	71.0	64.66	58.33	41.5	
	SnapKV	19.24	36.51	43.61	46.83	36.62	23.11	22.62	21.17	24.03	45.0	88.59	40.09	6.0	71.5	63.75	58.65	40.46	
	+THINK (0.5)	18.73	33.83	41.47	43.72	27.98	20.91	20.59	21.56	22.25	15.5	84.62	33.82	7.0	71.5	57.01	56.97	36.09	
	+THINK (0.8)	9.48	6.59	18.62	18.28	8.32	9.2	17.11	15.37	16.46	0.0	43.94	8.6	2.21	34.62	33.43	35.47	17.36	
	+SPARK (0.5)	18.66	36.13	43.23	46.66	36.17	22.86	22.44	21.19	23.7	42.5	89.11	40.15	6.5	71.5	63.8	59.0	40.22	
KV-size 1024	+SPARK (0.8)	18.23	37.34	42.42	44.71	34.85	23.14	21.8	21.26	23.68	41.5	87.22	38.88	5.0	72.5	62.86	55.01	39.40	
	PyramidKV	21.79	44.6	45.96	48.33	43.63	25.82	30.42	22.45	26.96	72.0	88.69	41.59	6.0	71.5	62.21	48.72	43.79	
	+THINK (0.5)	22.48	40.56	47.94	45.83	34.95	23.19	27.55	22.54	25.6	53.5	84.88	32.7	7.78	71.0	53.9	51.54	40.37	
	+THINK (0.8)	6.37	5.53	13.73	12.53	5.47	3.16	16.97	14.21	17.11	0.0	23.03	7.54	1.73	13.0	29.67	27.51	12.35	
	+SPARK (0.5)	22.79	43.99	45.63	48.83	43.64	24.87	30.34	22.89	26.57	70.0	88.75	42.28	6.5	71.5	62.72	50.81	43.88	
	+SPARK (0.8)	22.73	44.1	47.2	46.47	40.51	22.81	26.66	22.72	24.87	68.0	88.63	40.44	5.5	72.0	59.61	42.44	42.17	
	StreamingLLM	18.05	28.35	25.3	38.35	31.0	12.31	24.1	20.26	25.92	52.5	71.87	38.91	5.5	61.5	55.89	48.71	34.91	
	ExpectedAttention	21.06	36.69	37.86	45.76	35.36	22.08	26.59	21.62	26.76	64.5	89.64	40.36	5.5	62.0	63.79	55.67	40.95	
	TOVA	20.78	37.49	46.34	48.92	41.96	21.91	25.15	21.72	26.36	69.0	89.33	41.83	7.0	71.5	64.13	57.03	43.15	
	SnapKV	21.39	39.89	44.54	48.78	43.51	23.76	24.61	21.92	25.64	55.5	88.51	40.79	6.0	72.5	63.76	56.05	42.32	
KV-size 2048	+THINK (0.5)	19.44	38.4	45.16	46.3	32.01	21.18	22.4	21.88	24.43	30.5	85.45	33.98	7.0	72.0	57.09	55.86	38.32	
	+THINK (0.8)	7.97	6.08	17.09	16.7	6.41	7.23	17.41	15.33	16.75	0.0	38.44	8.12	1.64	22.14	33.76	34.42	15.59	
	+SPARK (0.5)	21.9	38.92	45.22	48.69	41.27	24.25	24.65	21.92	25.88	55.0	88.8	41.22	6.5	72.0	63.43	56.22	42.24	
	+SPARK (0.8)	21.26	39.65	45.48	46.93	38.85	22.84	23.98	21.94	25.37	54.0	87.93	39.34	5.0	72.0	63.66	51.97	41.26	
	PyramidKV	21.79	44.6	46.0	48.33	43.63	25.82	30.42	22.45	26.53	72.0	88.69	41.59	6.0	71.5	61.87	48.72	43.75	
	+THINK (0.5)	22.48	40.56	47.78	45.83	34.95	23.19	27.55	22.54	25.25	53.5	84.49	32.58	7.78	71.0	54.33	51.54	40.33	
	+THINK (0.8)	6.37	5.53	13.75	12.53	5.44	3.16	16.97	14.21	16.88	0.0	23.03	7.55	1.73	13.0	29.59	27.51	12.33	
	+SPARK (0.5)	22.53	43.84	45.97	47.83	43.64	24.87	30.06	22.9	26.82	70.0	89.28	41.87	6.5	71.5	61.4	50.84	43.74	
	+SPARK (0.8)	22.59	44.35	47.66	47.13	39.96	22.94	28.04	22.68	25.37	68.5	88.65	40.62	5.5	72.5	57.89	43.28	42.35	
	StreamingLLM	20.21	38.11	28.47	39.22	38.22	16.87	26.69	20.83	26.97	65.0	85.11	39.93	5.0	52.5	59.55	45.66	38.02	
KV-size 4096	ExpectedAttention	23.0	41.33	43.55	47.73	40.37	21.23	28.21	21.77	27.38	68.5	89.41	40.75	8.5	63.5	63.84	54.96	42.75	
	TOVA	21.83	41.99	45.37	48.47	43.54	23.92	27.41	22.4	27.17	67.5	89.21	42.14	6.5	72.0	64.16	55.53	43.7	
	SnapKV	22.66	41.71	46.74	48.86	43.68	23.76	27.09	22.39	27.28	62.0	88.3	41.45	6.0	72.0	63.64	53.8	43.21	
	+THINK (0.5)	20.06	40.36	48.02	45.55	36.94	22.3	24.23	22.33	25.74	47.5	84.41	33.97	6.14	71.5	56.41	55.49	40.06	
	+THINK (0.8)	6.08	4.94	15.32	13.56	5.43	6.54	17.19	15.0	16.77	0.0	31.5	7.76	2.01	15.21	32.81	33.7	13.99	
	+SPARK (0.5)	22.98	40.11	46.65	48.86	42.48	23.97	27.24	22.27	26.99	61.5	88.69	41.45	6.5	72.0	63.57	54.77	43.13	
	+SPARK (0.8)	23.65	41.91	46.59	47.13	41.33	21.84	25.99	22.58	26.81	59.0	88.04	39.62	5.0	72.5	62.74	48.69	42.09	
	PyramidKV	23.7	42.37	45.43	48.7	43.73	22.86	26.65	22.16	26.73	60.5	88.44	41.36	6.0	72.0	61.91	50.23	42.67	
	+THINK (0.5)	21.64	39.24	45.13	44.64	36.05	22.4	24.07	22.56	26.07	40.0	84.29	32.72	8.62	71.5	54.38	52.73	39.13	
	+THINK (0.8)	6.55	4.91	14.13	13.94	6.65	5.54	17.1	14.68	16.96	0.0	28.27	7.91	1.73	21.6	29.64	28.33	13.62	
	+SPARK (0.5)	23.3	40.47	41.47	47.72	43.38	23.49	25.5	21.85	25.49	59.5	88.02	41.41	6.0	71.0	61.79	51.52	41.99	
	+SPARK (0.8)	21.93	41.48	45.24	46.2	41.5	22.38	23.08	21.74	25.83	55.5	86.79	39.72	5.0	72.5	59.55	44.35	40.8	

Table 6: Performance comparison on LLaMA-3-8B-Instruct at LongBench. **SPARK** (λ) and **THINK**(λ) denote the channel-wise key cache pruning ratio λ .

Method	Single-Document QA				Multi-Document QA				Summarization			Few-shot Learning			Synthetic		Code		
	NrtvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	Pre	Lcc	RR-P	Avg.		
-	Vanilla	30.84	47.4	56.07	59.3	50.23	32.12	34.81	24.84	27.15	72.5	81.27	44.47	11.25	100.0	64.7	58.77	49.73	
KV-size 128	StreamingLLM	14.2	22.37	23.51	34.93	30.51	9.4	17.76	20.2	18.75	24.5	81.4	35.1	4.5	99.0	59.89	56.18	34.51	
	ExpectedAttention	19.62	26.06	31.65	40.95	25.31	15.1	24.01	21.99	24.38	21.0	87.16	38.22	5.0	97.67	44.09	40.46	35.17	
	TOVA	26.14	26.54	46.7	47.0	33.23	18.31	21.49	21.83	20.73	37.5	86.75	40.78	4.0	89.0	61.43	58.43	39.99	
	AdaSnapKV	20.3	24.27	39.46	49.14	36.34	17.8	18.1	21.04	20.26	25.0	84.45	39.12	4.5	96.5	62.11	61.76	38.76	
	SnapKV	14.81	22.58	39.17	45.51	33.78	10.46	17.54	20.27	18.84	26.5	85.27	38.17	5.5	94.0	61.63	57.79	36.99	
	+THINK (0.5)	15.52	20.21	37.06	41.55	32.17	12.43	16.7	20.26	18.22	11.5	74.44	33.91	3.5	94.5	51.45	49.12	33.28	
	+THINK (0.8)	11.24	9.91	21.63	23.92	10.32	5.27	13.04	13.95	13.92	0.0	47.82	11.94	1.38	80.89	32.36	31.77	20.59	
	+SPARK (0.5)	15.48	21.07	38.47	45.86	33.46	10.57	17.87	20.5	18.26	25.0	83.51	38.03	6.5	93.5	60.19	57.31	36.6	
	+SPARK (0.8)	13.09	15.89	25.61	34.04	23.21	8.12	12.2	14.45	12.25	16.0	66.85	25.26	3.0	71.0	37.63	44.72	26.46	
	PyramidKV	30.9	48.14	56.19	59.16	50.73	32.56	34.74	24.82	27.18	71.0	82.32	44.89	10.83	100.0	64.65	59.33	49.84	
KV-size 512	+THINK (0.5)	30.94	48.36	55.06	55.76	49.81	30.55	33.39	26.05	26.56	64.5	87.36	38.68	10.11	99.5	49.42	46.87	47.06	
	+THINK (0.8)	11.62	7.33	12.86	17.06	6.56	6.04	17.57	15.81	16.92	0.0	52.85	8.94	2.0	61.54	28.23	27.47	18.3	
	+SPARK (0.5)	30.96	47.79	56.29	59.22	50.2	32.88	34.69	24.94	26.6	71.0	81.12	44.74	13.6	99.5	62.36	55.66	49.47	
	+SPARK (0.8)	31.46	47.78	56.8	58.88	49.68	33.01	33.07	25.32	26.28	70.0	79.88	43.23	12.38	99.0	59.15	59.05	49.06	
	StreamingLLM	16.84	23.76	24.7	39.54	31.5	10.49	23.39	20.51	24.13	46.0	82.56	38.24	4.5	96.5	65.78	62.7	38.2	
	ExpectedAttention	24.6	37.46	35.47	46.79	40.86	19.36	27.5	22.13	26.28	49.5	90.42	40.63	4.5	90.5	59.19	51.2	41.65	
	TOVA	30.63	39.32	54.32	51.82	43.1	27.17	25.3	22.48	24.62	58.5	82.64	44.29	6.75	99.5	65.53	61.08	46.07	
	AdaSnapKV	27.36	39.5	52.65	57.46	48.36	28.75	24.34	23.3	24.67	46.0	82.42	41.73	9.0	99.5	66.58	62.59	45.89	
	SnapKV	27.74	38.03	52.23	56.96	44.97	24.94	24.05	23.26	24.29	42.0	83.1	40.92	8.0	99.5	67.21	61.42	44.91	
	+THINK (0.5)	26.29	36.37	49.56	55.67	41.8	25.18	22.67	22.5	23.43	38.5	88.47	38.88	5.25	99.5	55.97	51.55	42.6	
KV-size 1024	+THINK (0.8)	15.96	12.02	20.63	28.4	5.7	12.1	16.65	16.03	16.74	0.0	64.46	10.95	3.88	90.16	33.15	32.12	23.68	
	+SPARK (0.8)	24.62	32.79	37.63	50.58	36.67	24.3	20.23	18.67	19.0	34.0	67.34	32.05	6.0	75.5	51.75	51.68	36.43	
	PyramidKV	30.9	48.14	56.19	59.16	50.73	32.56	34.74	24.82	27.09	71.0	82.32	44.89	10.83	100.0	64.65	59.33	49.83	
	+THINK (0.5)	30.94	48.36	55.06	55.76	49.81	30.55	33.39	26.05	26.45	64.5	87.36	38.68	10.11	99.5	49.42	46.87	47.05	
	+THINK (0.8)	11.62	7.33	12.86	17.06	6.56	6.04	17.57	15.81	16.8	0.0	52.85	8.94	2.0	61.54	28.23	27.47	18.29	
	+SPARK (0.5)	30.8	47.6	56.74	59.47	50.2	33.59	34.45	25.03	26.67	71.0	82.1	44.94	14.1	99.5	62.41	56.06	49.67	
	+SPARK (0.8)	30.88	47.52	57.03	58.54	49.19	32.03	33.39	25.48	26.06	70.0	80.55	43.21	11.12	99.5	60.21	58.0	48.92	
	StreamingLLM	17.96	29.67	30.09	41.9	33.6	12.12	26.0	20.6	25.74	53.0	85.93	40.21	5.0	91.0	66.58	62.56	40.12	
	ExpectedAttention	26.99	40.54	41.78	51.37	43.31	22.91	29.31	22.93	26.96	54.5	90.64	42.71	5.0	95.5	64.23	56.58	44.7	
	TOVA	30.72	42.18	56.18	54.63	49.84	25.16	27.68	23.1	26.21	62.5	82.18	44.19	7.75	99.5	65.55	60.57	47.37	
KV-size 2048	AdaSnapKV	30.19	44.59	54.31	58.31	48.01	29.7	27.07	23.39	26.27	57.5	78.69	43.19	9.5	100.0	66.74	62.6	47.5	
	SnapKV	30.07	43.95	55.24	57.89	48.15	28.09	26.72	23.04	25.91	58.0	82.17	41.79	10.06	99.5	66.71	60.64	47.13	
	+THINK (0.5)	30.34	42.13	50.49	54.82	47.24	26.57	25.27	23.12	25.23	49.5	85.55	38.52	7.56	99.5	54.59	51.42	44.49	
	+THINK (0.8)	14.68	10.65	16.96	25.68	7.06	9.75	17.73	16.01	17.13	0.0	60.02	10.47	4.5	85.42	33.49	30.72	22.52	
	+SPARK (0.5)	30.23	44.91	54.68	58.91	47.57	29.89	26.81	23.29	26.05	56.5	79.05	41.95	9.56	99.5	66.19	60.3	47.21	
	+SPARK (0.8)	30.63	43.51	54.81	57.89	46.01	28.87	25.73	23.45	25.17	54.5	81.61	40.6	8.88	99.5	65.97	61.3	46.78	
	PyramidKV	30.9	48.14	56.32	59.16	50.73	32.56	34.74	24.82	26.91	71.0	82.32	44.9	10.83	100.0	64.12	59.33	49.8	
	+THINK (0.5)	30.94	48.36	55.22	55.76	49.81	30.55	33.39	26.05	26.15	64.5	87.36	38.71	10.11	99.5	49.08	46.87	47.02	
	+THINK (0.8)	11.62	7.33	13.03	17.13	5.97	6.04	17.57	15.81	16.56	0.0	52.85	8.95	2.0	61.54	27.74	27.47	18.23	
	+SPARK (0.5)	31.36	47.91	56.71	59.14	50.11	33.38	34.9	25.21	25.79	70.5	79.37	44.68	13.1	99.5	60.68	55.88	49.26	
	+SPARK (0.8)	31.1	47.72	55.73	58.1	49.31	32.15	33.15	25.48	25.12	69.5	80.96	43.59	13.38	100.0	60.34	57.83	48.97	

Table 7: Performance comparison on LLaMA-3.1-8B-Instruct at LongBench.

Method	Single-Document QA			Multi-Document QA			Summarization			Few-shot Learning			Synthetic			Code		
	NrtvQA	Qasper	MF-en	HotpotQA	2WikiQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	Pre	Lcc	Rb-P	Avg.	
LLaMA-3.1-70B-Instruct																		
KV-size 128	Vanilla	36.42	49.85	55.65	64.4	68.55	46.9	35.28	24.23	26.74	77.0	94.45	46.83	20.0	98.5	35.74	46.95	51.72
	StreamingLLM	19.55	21.96	25.95	39.65	39.61	18.13	18.21	18.98	18.94	5.5	91.61	37.87	10.5	97.5	59.35	52.39	35.98
	ExpectedAttention	20.92	25.17	29.53	32.91	35.18	7.08	23.17	15.5	24.47	20.0	92.53	38.29	13.5	67.5	38.39	40.08	32.76
	TOVA	32.92	34.58	48.6	57.88	56.65	38.8	20.65	21.19	18.87	33.0	94.02	43.09	7.5	93.5	62.76	60.25	45.27
	SnapKV	21.76	23.32	36.57	50.53	44.15	22.23	18.2	19.09	18.92	20.5	92.61	38.95	9.5	98.5	56.55	55.16	39.16
	+THINK (0.5)	20.4	20.6	35.23	47.79	41.39	21.6	17.61	18.34	18.64	5.0	91.4	35.5	11.0	96.75	53.23	50.44	36.56
	+THINK (0.8)	13.09	9.1	26.23	36.04	22.66	10.4	15.09	13.06	14.29	0.0	56.46	10.67	0.0	19.17	35.57	33.3	19.7
	+SPARK (0.5)	20.01	22.88	37.19	50.54	43.07	19.73	18.1	18.96	18.99	21.0	93.06	39.05	9.0	98.5	53.57	54.24	38.62
	+SPARK (0.8)	19.04	19.74	33.94	49.59	39.51	19.06	17.11	16.8	17.62	3.5	93.29	32.85	8.5	96.0	50.71	48.28	35.35
KV-size 512	PyramidKV	36.53	49.06	55.67	65.39	67.96	46.6	35.25	24.25	26.95	77.5	94.35	47.11	21.0	98.5	36.2	46.77	51.82
	+SPARK (0.5)	35.99	48.51	55.18	65.02	67.8	46.84	35.01	24.14	26.87	77.0	93.85	46.5	19.0	98.5	35.37	45.39	51.31
	StreamingLLM	20.08	28.43	27.65	45.26	43.04	22.5	24.35	19.64	24.2	47.5	92.26	40.67	11.0	97.5	63.09	55.94	41.44
	TOVA	32.54	43.81	50.85	54.86	62.61	24.81	17.48	20.13	24.07	61.5	94.1	47.36	3.5	16.5	52.99	62.44	41.85
	SnapKV	33.7	44.46	49.81	63.7	64.26	41.93	24.81	21.87	24.29	58.0	93.95	45.21	16.0	98.5	46.84	58.94	49.14
	+THINK (0.5)	33.54	40.38	51.09	60.45	60.9	38.23	24.17	21.98	23.71	40.0	92.14	41.78	15.0	98.5	61.99	59.7	47.72
	+THINK (0.8)	17.39	5.6	25.45	41.4	22.2	14.28	18.63	13.48	18.66	0.0	25.97	7.57	10.0	87.5	33.89	32.15	23.39
	+SPARK (0.5)	33.79	43.77	49.88	63.6	64.53	41.56	24.74	22.29	24.21	57.0	93.95	44.3	16.5	98.5	45.62	58.13	48.9
	+SPARK (0.8)	32.08	41.45	49.5	59.84	56.91	36.55	22.99	21.97	23.02	38.0	93.2	39.29	15.0	98.0	56.77	56.54	46.32
KV-size 1024	PyramidKV	36.53	49.06	55.67	65.39	67.96	46.6	35.25	24.25	26.77	77.5	94.35	47.11	21.0	98.5	36.2	46.77	51.81
	StreamingLLM	23.1	32.35	29.8	51.12	47.22	22.36	26.4	20.12	25.9	60.5	93.72	41.95	14.0	96.5	60.28	59.95	44.08
	TOVA	27.31	47.6	55.04	61.25	66.88	37.54	26.12	21.12	26.04	70.0	94.1	47.3	15.0	98.5	42.65	58.25	49.67
	SnapKV	35.17	48.76	52.53	65.03	66.14	44.55	28.01	22.35	26.17	65.5	93.95	45.03	15.5	98.5	40.57	55.82	50.22
	+THINK (0.5)	36.05	46.36	52.3	62.73	62.43	40.67	26.98	23.17	25.17	53.0	93.14	42.39	13.5	99.0	63.86	59.65	50.02
	+SPARK (0.5)	35.26	47.63	52.34	64.76	66.51	44.68	27.88	23.19	26.18	66.0	93.95	45.54	14.5	98.5	40.12	55.21	50.14
	+SPARK (0.8)	35.11	45.39	51.37	59.55	60.45	40.1	24.67	22.79	24.87	52.5	92.95	36.9	12.5	98.5	54.81	55.4	47.99
	PyramidKV	36.53	49.06	55.56	65.39	67.96	46.6	35.25	24.25	26.64	77.5	94.35	47.12	21.0	98.5	36.54	46.77	51.81
KV-size 2048	StreamingLLM	25.53	41.15	38.29	52.91	53.74	26.76	29.14	20.82	26.34	66.5	93.3	43.55	17.5	97.0	47.63	60.9	46.32
	TOVA	34.03	48.95	55.37	63.53	67.43	46.93	31.0	23.17	26.68	76.0	94.35	47.0	16.5	98.5	37.87	53.94	51.33
	SnapKV	36.49	50.02	53.43	65.58	65.28	46.99	30.75	23.49	26.35	70.5	94.45	46.1	17.5	98.5	37.22	53.41	51.0
	+THINK (0.5)	36.49	48.46	52.92	65.15	66.19	46.28	30.82	23.83	26.73	70.5	93.95	46.41	18.0	98.5	37.09	52.31	50.85
	+SPARK (0.5)	35.66	50.33	51.34	62.69	62.64	41.71	28.99	23.74	25.93	60.5	93.14	41.99	16.5	99.0	63.66	59.72	51.1
	+SPARK (0.8)	35.24	48.11	51.69	59.3	59.89	39.86	26.44	23.09	25.46	56.0	93.2	35.72	16.0	98.0	50.07	53.62	48.23
	PyramidKV	37.11	48.66	55.56	64.38	67.06	46.67	30.09	23.38	26.51	67.0	92.87	46.18	18.0	98.5	36.52	53.64	50.76

Table 8: Performance comparison on LLaMA-3.1-70B-Instruct at LongBench.

Method	Single-Document QA				Multi-Document QA				Summarization				Few-shot Learning			Synthetic		Code	
	NrrvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	Pre	Lcc	RB-P	Avg.		
Qwen-3-8B																			
KV-size 128	Vanilla	29.07	44.26	55.57	62.3	48.11	35.81	33.59	24.52	24.9	69.0	88.9	41.04	9.0	91.43	68.99	67.93	49.65	
	StreamingLLM	14.81	19.68	24.18	28.9	29.81	9.55	15.78	18.72	15.58	17.75	43.86	34.02	3.0	40.46	63.21	60.35	27.48	
	ExpectedAttention	16.9	27.23	29.24	25.32	14.29	9.95	23.55	20.31	21.48	8.5	77.06	35.23	4.27	12.33	46.07	41.4	25.82	
	TOVA	18.09	25.8	39.71	44.34	34.02	17.83	17.11	19.33	14.55	17.0	88.03	38.51	7.5	84.92	62.42	59.21	36.77	
	SnapKV	17.12	23.54	33.8	40.24	34.32	15.47	16.15	19.12	15.69	21.0	72.55	36.93	3.5	74.3	63.7	59.03	34.15	
	+THINK (0.5)	16.15	23.52	30.33	38.71	31.45	16.99	15.25	19.19	14.43	9.5	68.64	29.54	1.5	72.62	56.51	53.93	31.14	
	+THINK (0.8)	11.51	14.43	18.33	26.1	20.52	7.59	12.43	17.43	11.34	0.5	27.87	9.13	3.0	43.5	29.13	28.46	17.58	
	+SPARK (0.5)	16.82	23.08	33.76	40.25	34.49	15.61	15.99	18.99	15.3	19.5	72.26	36.61	3.0	74.23	62.99	58.48	33.84	
	+SPARK (0.8)	17.16	23.03	32.66	38.41	33.53	14.7	15.69	18.92	15.55	18.5	64.76	35.5	1.0	70.79	62.24	58.54	32.56	
	PyramidKV	29.76	44.26	56.27	61.52	48.17	33.64	33.54	24.42	24.61	68.0	88.52	41.65	10.0	91.92	67.0	66.66	49.37	
KV-size 512	+THINK (0.5)	24.74	42.12	51.07	60.22	44.99	31.28	32.47	23.91	24.03	69.0	86.55	28.49	8.0	99.75	61.04	60.23	46.74	
	+SPARK (0.5)	29.12	43.5	55.57	62.14	47.95	33.49	33.39	24.34	24.09	68.0	89.07	41.08	10.0	92.67	66.21	65.86	49.15	
	+SPARK (0.8)	28.36	44.03	53.46	59.63	49.67	31.46	33.08	23.82	24.22	68.0	89.6	39.84	10.0	95.6	66.03	64.27	48.82	
	StreamingLLM	16.91	23.14	26.92	32.25	32.57	10.41	22.37	19.71	21.29	45.0	62.68	36.52	7.0	34.58	67.59	63.55	32.66	
	ExpectedAttention	21.17	31.86	36.85	44.82	37.1	20.29	28.9	21.23	24.11	45.0	85.71	38.66	3.26	21.33	56.83	53.56	35.67	
	TOVA	22.3	37.04	48.71	54.34	45.15	23.84	22.8	20.8	20.63	51.0	88.88	42.25	4.5	98.06	68.85	66.06	44.7	
	SnapKV	25.11	34.04	47.47	55.54	40.39	26.09	22.83	21.32	21.2	48.5	88.2	38.69	7.58	97.31	68.56	67.64	44.4	
	+THINK (0.5)	22.26	32.85	45.24	54.57	38.56	27.18	20.81	20.85	19.09	34.0	86.6	31.57	4.5	99.5	61.68	60.95	41.26	
	+THINK (0.8)	10.25	17.31	24.36	29.42	20.44	11.71	16.61	17.66	14.04	0.0	50.87	10.05	4.5	77.25	30.43	33.04	23.0	
	+SPARK (0.5)	24.72	33.56	46.53	54.93	41.6	26.29	22.75	20.92	21.16	49.0	89.3	38.22	8.03	96.78	67.98	67.25	44.31	
	+SPARK (0.8)	24.6	32.77	45.96	56.33	40.4	23.76	22.47	20.75	20.93	42.5	87.3	37.15	7.02	97.83	67.51	66.52	43.36	
KV-size 1024	PyramidKV	29.76	44.26	56.27	61.52	48.17	33.64	33.54	24.42	24.28	68.0	88.52	41.65	10.0	91.92	67.0	66.66	49.35	
	+THINK (0.5)	24.74	42.12	51.07	60.22	44.99	31.28	32.47	23.91	23.82	69.5	86.39	28.22	7.5	99.75	61.13	60.12	46.7	
	+SPARK (0.5)	29.03	43.77	55.1	62.07	48.21	33.94	33.47	24.4	24.17	69.0	88.57	41.1	9.5	91.92	66.75	66.21	49.2	
	+SPARK (0.8)	28.7	43.97	53.29	60.98	48.45	31.44	32.63	23.66	24.25	67.0	89.43	40.03	9.5	95.1	66.01	64.77	48.7	
	StreamingLLM	19.31	25.15	29.14	33.38	33.8	11.9	25.51	20.71	23.55	53.5	71.95	37.15	8.5	31.2	68.17	65.42	34.9	
	ExpectedAttention	24.01	35.71	42.89	50.51	42.38	24.08	30.44	21.7	24.71	63.0	86.36	39.64	4.36	29.07	63.3	59.55	40.11	
	TOVA	25.0	39.69	49.96	58.53	45.63	29.51	26.39	21.41	23.19	62.5	88.25	42.52	7.66	95.72	69.18	67.44	47.04	
	SnapKV	25.59	39.64	52.09	56.63	44.85	32.69	26.23	22.04	23.17	61.5	89.18	39.64	8.6	96.88	69.69	69.15	47.35	
	+THINK (0.5)	23.51	36.86	49.17	57.85	42.75	30.57	23.84	22.04	22.05	51.5	86.59	31.04	5.0	100.0	61.96	61.05	44.11	
	+THINK (0.8)	10.81	15.51	24.45	29.39	19.26	13.58	17.51	18.24	14.6	0.0	42.82	9.45	3.5	66.42	28.65	32.29	21.65	
KV-size 2048	+SPARK (0.5)	25.71	39.83	52.44	55.94	45.77	32.51	26.25	22.2	23.2	60.0	89.2	39.11	7.59	97.54	68.66	68.98	47.18	
	PyramidKV	29.76	44.26	56.05	61.52	48.17	33.64	33.54	24.42	23.88	68.0	88.52	41.61	10.0	91.92	66.83	66.66	49.3	
	+THINK (0.5)	25.17	42.4	49.81	61.18	46.02	31.23	32.72	23.82	23.48	69.5	86.39	28.22	7.5	99.75	61.69	60.12	46.81	
	+SPARK (0.5)	29.32	43.79	54.92	62.15	48.89	33.4	33.25	24.34	23.79	68.5	88.54	41.28	10.0	92.29	66.64	66.16	49.2	
	+SPARK (0.8)	28.16	43.57	53.83	60.06	46.95	31.48	33.07	24.07	23.62	68.0	89.1	39.93	8.5	94.6	65.76	64.84	48.47	
	StreamingLLM	22.55	31.89	35.35	39.99	39.72	16.92	28.83	21.35	24.57	62.0	80.83	38.22	7.5	36.92	67.1	65.52	38.7	
	ExpectedAttention	26.73	40.61	48.65	54.65	43.82	28.51	32.08	22.71	24.86	67.17	87.4	40.79	6.53	49.12	66.46	63.74	43.99	
	TOVA	27.2	42.68	51.96	59.65	47.8	32.41	29.54	22.55	24.47	68.0	89.0	42.45	10.1	95.27	67.7	66.47	48.58	
	SnapKV	28.89	42.56	53.93	60.47	47.73	32.65	29.68	22.85	24.57	67.0	89.77	40.67	6.85	96.83	68.05	67.19	48.73	
	+THINK (0.5)	25.77	40.45	50.64	60.34	43.55	32.7	27.49	22.63	23.81	62.5	86.51	30.53	6.0	100.0	62.3	62.6	46.11	
KV-size 4096	+THINK (0.8)	9.39	11.95	21.63	26.22	18.33	11.71	17.62	17.58	14.73	0.0	33.65	9.6	3.0	52.5	26.89	29.85	19.04	
	+SPARK (0.5)	28.11	43.24	53.07	61.07	49.42	34.31	29.37	22.73	24.28	67.5	89.43	39.8	5.82	97.21	68.12	68.47	48.87	
	PyramidKV	25.88	39.26	52.05	57.87	42.73	29.2	27.37	22.58	24.09	60.0	89.66	40.17	7.1	97.18	67.5	65.81	46.78	
	+THINK (0.5)	23.57	38.32	51.62	56.82	38.67	27.5	25.58	22.47	23.42	55.0	86.82	30.94	6.0	99.75	61.38	60.34	44.26	
	+SPARK (0.5)	25.88	40.06	53.1	57.91	42.7	28.85	27.37	22.59	24.2	62.5	88.83	39.68	8.0	97.85	66.95	65.9	47.02	
	+SPARK (0.8)	23.77	39.99	50.94	57.31	42.23	24.97	26.9	22.57	23.72	55.0	89.6	38.05	7.0	98.42	65.87	64.71	45.69	

Table 9: Performance comparison on Qwen3-8B at LongBench.

Method	Single-Document QA				Multi-Document QA				Summarization			Few-shot Learning			Synthetic		Code		
	NrtvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PRe	Lcc	RB-P	Avg.		
Qwen-3-32B																			
KV-size 128	StreamingLLM	17.04	21.12	26.96	30.13	37.41	9.69	15.18	19.17	16.59	17.5	21.37	29.11	3.0	85.01	25.86	28.1	25.2	
	TOVA	30.32	31.87	42.71	55.13	48.72	28.31	17.68	20.31	16.41	21.5	71.92	32.0	5.5	91.0	35.25	36.03	36.54	
	SnapKV	19.95	24.41	35.94	39.32	39.29	11.23	16.39	19.46	16.53	18.25	35.29	31.86	4.5	91.62	40.0	44.29	30.52	
	+THINK (0.5)	20.79	23.39	36.97	33.74	35.55	11.15	15.4	19.71	15.74	4.0	31.86	33.12	4.5	89.03	41.18	43.81	28.75	
	+THINK (0.8)	13.79	18.77	20.3	25.04	22.29	8.88	11.24	17.8	12.1	0.0	21.62	13.15	2.5	70.9	26.54	28.88	19.61	
	+SPARK (0.5)	20.57	24.09	35.54	38.06	38.71	10.54	16.46	19.45	16.52	18.5	32.18	31.86	4.5	91.57	40.66	44.06	30.2	
	+SPARK (0.8)	21.78	22.85	34.93	38.07	37.8	12.36	16.4	19.22	16.28	17.0	29.39	31.48	3.5	86.38	42.51	43.12	29.57	
KV-size 512	PyramidKV	31.44	47.85	51.49	53.25	55.54	28.19	33.19	24.14	25.39	71.0	77.32	39.09	16.5	99.75	24.4	30.59	44.32	
	StreamingLLM	17.91	25.73	29.19	31.66	39.0	11.66	21.19	19.14	22.31	46.5	27.46	32.05	6.5	77.11	27.56	29.59	29.04	
	TOVA	31.83	40.26	48.49	54.42	54.98	31.49	23.49	21.75	22.35	62.5	78.01	37.9	11.0	98.18	28.21	32.68	42.35	
	SnapKV	30.06	39.74	47.38	55.96	50.59	28.89	23.35	21.61	22.29	40.0	72.23	36.36	11.0	93.07	28.24	37.69	39.9	
	+THINK (0.5)	26.8	38.3	47.0	53.64	42.53	26.07	21.81	22.14	20.74	30.5	77.94	37.41	11.5	98.05	30.5	36.47	38.84	
	+THINK (0.8)	14.58	21.64	23.01	28.87	17.27	13.34	14.75	18.1	15.12	0.0	33.46	10.87	7.0	85.66	22.56	22.71	21.81	
	+SPARK (0.5)	30.6	38.81	46.44	55.66	49.99	28.92	23.56	21.65	22.54	39.0	70.17	34.76	11.0	93.31	27.35	37.7	39.47	
	PyramidKV	31.44	47.85	51.49	53.25	55.54	28.19	33.19	24.14	25.09	71.0	77.32	39.09	16.5	99.75	24.4	30.59	44.3	
KV-size 1024	StreamingLLM	20.66	27.99	30.63	35.26	38.14	12.78	23.67	20.13	24.05	56.5	37.11	34.17	8.0	63.12	28.85	32.81	30.87	
	TOVA	31.03	44.82	50.94	55.29	57.49	30.37	26.25	22.43	24.25	64.5	77.86	38.98	15.5	98.54	24.59	29.21	43.25	
	SnapKV	31.17	44.08	48.35	56.13	53.94	30.03	26.76	22.58	24.54	50.25	79.74	36.79	14.0	95.29	23.97	33.39	41.94	
	+THINK (0.5)	28.24	41.85	47.89	54.1	45.95	27.42	24.57	22.92	23.6	45.5	82.39	38.09	12.0	99.75	26.13	36.3	41.04	
	+THINK (0.8)	15.01	22.06	20.19	26.13	15.92	11.32	16.26	17.51	15.45	0.0	29.65	7.53	7.0	87.57	20.93	20.67	20.83	
	+SPARK (0.5)	30.62	44.09	47.06	56.38	52.26	30.51	27.0	22.33	24.64	51.0	79.55	35.87	15.5	96.32	24.26	32.95	41.9	
	+SPARK (0.8)	30.18	43.72	47.09	56.42	50.13	30.06	26.26	22.74	24.17	46.17	76.16	-1	-1	-1	-1	41.19		
	PyramidKV	31.44	47.85	51.3	53.25	55.7	28.19	33.19	24.14	24.82	71.0	77.65	39.06	16.5	99.75	23.71	30.59	44.26	
KV-size 2048	StreamingLLM	23.1	35.85	35.58	37.33	44.36	16.88	27.19	21.03	24.82	60.5	42.44	36.5	13.5	62.0	28.88	31.62	33.85	
	TOVA	32.22	46.91	51.48	55.72	55.69	30.93	29.35	23.62	25.08	67.5	77.7	38.79	16.0	99.67	24.09	30.04	44.05	
	SnapKV	32.36	45.84	51.04	54.21	55.28	31.22	29.48	23.63	24.96	62.5	79.03	38.09	14.0	98.1	23.75	33.19	43.54	
	+THINK (0.5)	28.95	43.23	48.36	54.22	45.77	29.25	28.16	23.56	24.72	60.17	84.44	37.95	11.0	100.0	24.42	34.04	42.39	
	+THINK (0.8)	14.06	21.21	17.2	23.84	15.96	9.55	16.75	17.33	15.29	0.5	30.04	4.53	9.0	89.79	18.22	19.38	20.17	
	+SPARK (0.5)	32.29	45.76	50.09	55.42	54.04	31.44	29.58	23.66	25.18	61.5	77.75	36.97	13.0	98.32	25.0	33.2	43.33	
	PyramidKV	29.62	43.39	50.28	55.9	51.83	28.31	26.45	22.21	24.39	47.67	76.77	36.73	16.0	98.35	24.38	38.59	41.93	

Table 10: Performance comparison on Qwen3-32B at LongBench.

Method	Niah1	Niah2	Niah3	MKey1	MKey2	MKey3	MValue	MQuery	VT	CWE	FWE	QA1	QA2	Avg.	
16K															
Vanilla	100.0	100.0	100.0	99.6	100	99.2	99.1	99.0	99.8	88.9	90.0	81.0	57.2	93.36	
20% KV cache	StreamingLLM	18.8	17.4	19.0	20.2	20.0	18.4	18.25	18.2	32.84	0.18	81.33	31.4	33.6	25.35
	ExpectedAttention	99.2	42.0	3.4	33.8	57.0	0.8	9.35	21.1	66.12	54.46	70.6	72.0	48.2	44.46
	TOVA	100.0	100.0	97.8	99.4	96.8	0.4	98.9	99.25	99.76	54.04	90.8	77.4	54.6	82.24
	SnapKV	100.0	100.0	10.0	99.8	97.2	63.2	97.7	99.45	97.36	53.92	85.73	80.8	57.2	80.18
	+THINK(0.5)	96.6	99.6	9.4	99.0	92.2	55.4	98.55	98.25	94.84	29.12	88.87	76.0	50.6	76.03
	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.0	0.0	0.32	0.0	18.8	20.2	3.03
	+SPARK (0.5)	100.0	100.0	10.2	99.4	96.6	62.8	98.05	99.45	97.64	53.8	86.2	80.8	56.0	80.07
	+SPARK (0.8)	100.0	99.8	9.6	99.2	94.2	49.4	98.1	98.75	96.64	41.12	87.07	80.0	53.8	77.51
	PyramidKV	100.0	100.0	5.0	99.8	98.2	55.0	98.6	99.35	98.6	16.88	87.0	80.0	57.2	76.59
	+THINK(0.5)	97.2	100.0	4.8	99.4	93.0	49.2	98.7	98.75	96.16	8.46	88.33	76.2	52.4	74.05
50% KV cache	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.24	0.0	14.8	19.4	2.65
	+SPARK (0.5)	99.2	99.2	5.2	99.4	97.6	54.4	97.95	98.7	98.16	16.84	86.27	79.6	56.8	76.1
	+SPARK (0.8)	99.4	98.8	5.2	99.2	94.4	44.2	97.1	97.7	95.24	12.08	86.2	78.4	54.0	73.99
	StreamingLLM	47.0	45.4	49.4	51.2	48.6	48.0	48.1	48.0	68.56	10.84	85.13	82.6	43.4	52.02
	ExpectedAttention	100.0	93.0	18.0	93.4	98.0	42.6	72.55	77.15	97.96	81.52	83.87	80.0	54.6	76.36
	TOVA	100.0	100.0	100.0	99.8	99.8	48.6	98.85	98.9	99.8	90.6	91.87	80.6	56.6	89.65
	SnapKV	100.0	100.0	72.0	99.6	100.0	97.8	98.5	99.15	99.6	84.0	90.4	81.8	57.2	90.77
	+THINK(0.5)	97.4	99.8	69.4	99.4	98.4	96.0	99.0	97.9	98.2	69.06	91.67	78.2	51.4	88.14
	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.0	0.0	1.62	0.07	10.4	14.6	2.06
	+SPARK (0.5)	100.0	99.6	71.8	98.6	99.8	97.8	98.65	99.0	99.68	84.2	88.27	81.6	56.8	90.45
	+SPARK (0.8)	99.0	95.0	70.0	98.2	96.8	94.2	98.65	98.6	99.24	75.26	91.27	80.6	55.2	88.62
8K	PyramidKV	100.0	100.0	48.6	99.8	100.0	95.2	99.2	99.1	99.8	52.88	90.13	81.0	57.4	86.39
	+THINK(0.5)	98.2	99.6	47.4	99.6	98.8	92.4	99.15	97.8	98.64	32.9	92.2	77.4	52.2	83.56
	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.0	0.0	0.74	0.0	9.6	13.4	1.83
	+SPARK (0.8)	99.8	100.0	47.4	99.6	99.8	95.6	99.2	99.05	99.8	52.8	90.27	80.8	57.2	86.26
	+SPARK (0.8)	100.0	100.0	47.8	99.8	99.8	93.4	99.15	99.15	99.28	47.38	90.33	80.2	54.0	85.41
	StreamingLLM	18.8	18.8	20.8	20.2	18.4	18.0	18.1	17.25	33.6	9.68	82.6	32.4	45.2	27.22
	ExpectedAttention	98.8	62.0	0.0	56.2	66.2	0.4	16.4	35.5	63.12	60.22	68.53	65.6	54.2	49.78
	TOVA	100.0	99.8	93.4	100.0	96.2	0.4	99.4	99.4	99.56	44.32	67.67	74.8	56.8	79.37
	SnapKV	100.0	99.2	2.6	100.0	97.4	36.0	96.15	99.6	94.76	62.04	70.73	81.2	61.8	77.04
	+THINK(0.5)	93.0	97.0	2.6	99.4	88.0	31.2	96.25	99.5	90.76	45.66	68.07	77.6	56.0	72.7
50% KV cache	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.16	0.0	26.4	25.4	4.0
	+SPARK (0.5)	100.0	99.2	2.6	100.0	97.0	34.6	96.15	99.65	95.48	61.68	70.73	81.2	61.0	76.87
	+SPARK (0.8)	93.0	92.0	2.6	95.8	88.4	25.0	89.6	92.05	85.44	47.82	66.4	76.8	51.2	69.7
	PyramidKV	100.0	99.8	2.4	100.0	98.2	27.8	98.4	99.65	94.24	32.44	66.67	81.2	62.6	74.11
	+THINK(0.5)	95.0	98.2	2.4	99.6	88.2	25.2	97.9	99.55	91.04	19.02	63.27	77.8	56.2	70.26
	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.16	0.0	26.2	24.6	3.92
	+SPARK (0.5)	100.0	99.6	2.4	99.8	97.8	28.0	98.1	99.65	93.84	31.64	66.13	79.0	61.8	73.67
	+SPARK (0.8)	97.2	96.6	2.4	99.2	93.6	20.4	94.3	97.4	88.76	21.06	63.67	74.8	54.4	69.52
	StreamingLLM	47.0	49.4	55.4	54.4	52.0	50.0	51.2	49.65	71.08	26.5	85.6	33.4	53.4	52.23
	ExpectedAttention	99.8	91.2	10.0	96.8	95.4	35.4	73.5	78.8	94.36	95.2	82.4	78.6	59.2	76.2
8K	TOVA	100.0	100.0	100.0	100.0	99.8	53.0	99.8	99.65	99.88	87.28	78.07	82.2	62.0	89.36
	SnapKV	100.0	100.0	48.0	100.0	99.6	92.8	99.0	99.7	98.8	92.48	83.27	82.6	62.6	89.14
	+THINK(0.5)	97.0	99.0	43.2	99.6	96.2	89.8	99.15	99.7	97.28	86.0	81.27	78.4	57.8	86.49
	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.0	0.0	3.26	0.0	19.2	21.0	3.35
	+SPARK (0.5)	100.0	100.0	47.8	100.0	99.6	93.2	98.8	99.55	98.92	92.48	83.07	82.2	61.4	89.0
	+SPARK (0.8)	100.0	99.8	43.0	100.0	99.2	85.6	97.6	99.7	97.56	88.5	82.27	79.8	57.8	86.99
	PyramidKV	100.0	100.0	24.6	100.0	99.8	87.4	99.8	99.6	99.0	69.54	79.73	82.8	61.6	84.91
	+THINK(0.5)	98.0	99.6	21.8	99.4	98.8	85.8	99.55	99.25	97.92	54.9	77.93	77.4	57.2	82.12
	+THINK(0.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.24	0.0	17.4	20.6	3.02
	+SPARK (0.5)	99.2	99.4	25.0	99.8	99.4	87.2	99.35	99.25	98.6	69.14	79.8	82.8	60.6	84.58
	+SPARK (0.8)	99.0	100.0	24.0	99.8	99.6	84.2	98.75	99.25	97.64	65.26	78.47	80.4	58.4	83.44

Table 11: RULER evaluation results on the LLaMA3.1-8B-Instruct model with SPARK under a 20% and 50 % KV cache budget with 8K and 16K input length.